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Life-Cycle Worker Flows and Cross-country Differences in Aggregate Employment*

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Abstract

We propose new data moments to measure the role of life-cycle worker flows between employment, unemployment and out of the labor force in shaping cross-country differences in aggregate employment. We then show that a suitably extended version of the Diamond-Mortensen-Pissarides model can capture well these data moments. Two features of the model are crucial for this result: heterogeneity in match quality and endogenous search intensity. We examine the implications of this model for the sources of employment dispersion across Europe's largest countries, assessing the contribution of factors related to (i) the production technology, (ii) search, and (iii) policies. The sources of cross-country employment dispersion differ substantially across ages. Technology factors account for most of the employment variance of youths and prime-age workers, whereas search and policies are the main drivers of employment differences for older individuals.

Key words: *Employment, Unemployment, Labor Force Participation, Life cycle, Worker Flows, Labor Market Institutions*.

JEL Classification: E02, E24, J21, J64, and J82.

1 Introduction

Aggregate employment differences across countries are largely driven by the two ends of the age spectrum: while prime-age employment rates are broadly similar, unemployment among younger workers and labor force participation rates of older individuals differ wildly across countries (see Cohen et al. [1997], OECD [2006], Chéron et al. [2009], Lalé [2018]). These facts are well known and highly influential when it comes to formulating policy proposals in order to improve aggregate employment performances.[1] Yet most applications of the Diamond-Mortensen-Pissarides (DMP) model abstract from the joint modeling of the life cycle and labor force participation decisions. As a result, these applications have little to say about the underlying demographics of the employment gap between countries, and the channels (higher unemployment vs. reduced labor force participation) through which it arises. They are also mostly silent on whether the employment effects of labor market policies are predicted to be uniform or heterogeneous across different age groups. This drastically limits the range of outcomes on which these DMP models can be tested against the data, as well as undermine their usefulness for the design and assessment of labor market policies.

With the objective to address these gaps in the literature, we proceed in two steps and make two contributions. First, we construct, for a large panel of countries, new data moments that characterize the role of life cycle worker flows between employment, unemployment and nonparticipation in shaping cross-country differences in aggregate employment. We then develop a DMP model cast in a life-cycle setting and featuring a labor force participation margin, which not only speaks to but captures well the new data moments. We demonstrate what model elements are crucial to match the data, and we also examine how they interact with the labor market policies incorporated in the model.

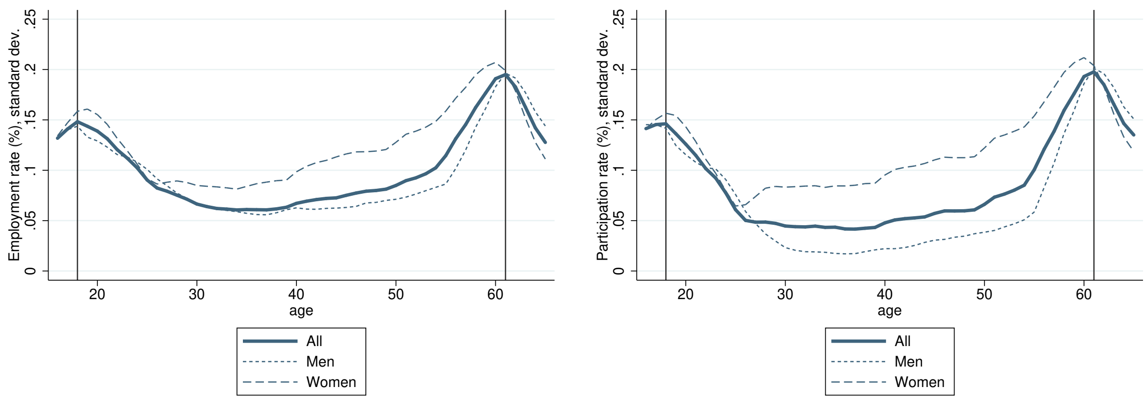
The empirical part of our analysis is based on survey microdata from 31 European countries. Figure 1 documents the much larger cross-country dispersion in employment rates at the two ends of the age spectrum found in these data. Besides illustrating the range of variation over the life cycle, the figure also suggests that a large share of the cross-country dispersion in employment comes from differences in labor force participation.

Our first contribution is empirical. To understand the patterns presented in Figure 1 better, we naturally relate them to the underlying worker flows between employment, unemployment and nonparticipation.[2] The challenge facing our analysis is that cross-country aggregate employment differences depend on the life-cycle worker flows in a non-linear fashion, and decompositions of the employment gap into the role of these flows are not unique.[3] We take advantage of the Shapley value to overcome this challenge. The Shapley value summarizes in a single

[1]See Bell and Blanchflower [2011], Burlon and Vilalta-Bufí [2016], Cahuc et al. [2013], and Caliendo and Schmidl [2016], as well as many OECD publications such as the OECD [2010] report on the barriers to employment for young workers and the OECD [2019] report on retirement policies and employment at older ages.

[2]The other sources of employment differences across countries are initial conditions, i.e. different rates of unemployment and labor force participation in the first age group (16 years-old in our analysis), and differences in the demographic structure of the labor force. We show in Section 2 that these two factors together explain less than 10 percent differences in aggregate employment across countries.

[3]With 3 labor market states (employment, unemployment, nonparticipation), there are 6 independent transition rates and hence $6! = 720$ ways to decompose the employment gap between two countries (Section 2).



(a) Employment **(b)** Labor force participation

Figure 1: Cross-country standard deviation of employment and labor force participation

NOTE: The figure shows the standard deviation of the employment rates and labor force participation rates at each age from 16 to 65 years across the 31 countries of our sample.

number the contribution of each worker flow to the cross-country employment variance. This approach – which, to our knowledge, has not been applied before to the study of cross-country employment differences – provides us with a set of new stylized facts that are directly and easily interpretable as well as interesting in their own rights. Furthermore, these facts are useful to inform or confront any life-cycle model of stock-flow (un)employment, such as the model that we develop in the second step of our analysis.

We find empirically that transitions out of employment and labor force participation are key to explaining aggregate employment differences. Specifically, for male workers, job separation rates, not job finding rates, are the main driver of cross-country differences in aggregate employment. They account for at least half of the dispersion. This result is somewhat in contrast with the labor search literature that puts the job-finding rate at the centre of our understanding of employment dynamics. For female workers, the picture is quite different: the cross-country variance of employment is chiefly explained by transitions from nonparticipation to employment. We should note that even for men, after adding up the variance contributions of transitions that involve being out of the labor force, the participation margin cannot be ignored – echoing the conclusions of Elsby et al. [2015], but in a life-cycle instead of business-cycle context. These findings underscore well our choice of a model that explicitly distinguishes unemployment from being out of the labor force.

In the second part, we develop a DMP model which contains a few non-standard ingredients. The model has a finite retirement horizon, endogenous search intensity and labor-force participation margins, permanent heterogeneity in match quality (subject to information frictions and learning), and utility- and match-specific productivity shocks. Crucially, we impose all the model primitives (technology, preferences, and the distribution of shocks) to be independent of age, allowing us to uncover fundamental, rather than proximate, sources of worker-flow variations and to conduct counterfactual policy analysis. We calibrate this model to the *aggregate* worker flows between employment, unemployment, and nonparticipation, and to employment *rates* by age. We do so for men and women in the four largest E.U. countries (France, Germany, Italy, Spain) and the U.K.

The calibrated model performs remarkably well at capturing the salient features of the untargeted data, that is to say the *twelve* transition rates (six for each gender) between the ages of 16 to 65 years in the *five* countries. In particular, the model predicts a declining life-cycle profile for transitions out of nonparticipation (into both unemployment and employment) and an increasing profile for transitions out of the labor force (from both unemployment and employment) as observed in our data by country and gender – in addition to generating plausible flows in and out of employment and unemployment. The combined role of endogenous search intensity with an exogenous finite retirement horizon and utility shocks is key in shaping the life-cycle transitions in and out of nonparticipation: the closer is retirement, the weaker the incentives to participate in market activities. This is what Chéron et al. [2011, 2013] have coined the 'horizon effect' in their analyses of unemployment-to-employment flows within the life-cycle DMP model – a mechanism that we generalize to a setup with a distinction between unemployment and nonparticipation.

The second contribution consists of the quantitative analysis of the model. We structurally decompose the employment gap between the countries of our analysis into factors related to (i) the technology of (market) production, (ii) the technology of search, matching, and home production, and (iii) labor market policies. This exercise also illuminates the roles of various ingredients of the model, highlighting those that are key for its good fit to the data.

Specifically, we decompose the employment differences by age and gender between each country and a hypothetical country with outcomes generated by the model where we impose average parameter values. This decomposition has three components reflecting the contribution of factors (i) to (iii). Using these decomposed employment gaps, we compute the variance contribution of each factor to the total employment variance, conditioning on age and gender. This exercise shows that the sources of employment differences differ greatly across demographic groups. Technology factors (i) account for most of the employment differences for young and prime-age workers, whereas search (ii) and policies (iii) are important contributors to the employment dispersion of older individuals. After the age of 40, the sources of employment variance differ greatly between men and women as search-related factors become strong positive contributors for the women's variance and technology a negative contributor. We find the opposite for prime-age men. This analysis shows the importance of studying employment outcomes at a disaggregated level to understand the sources of cross-country variation in aggregate employment rates.

Related literature. Our empirical analysis is related and contributes to a vast literature that studies labor market flows and aggregate employment dynamics. Two closely related papers in this literature are Elsby et al. [2013] and Choi et al. [2015]. Elsby et al. [2013] document cross-country differences in unemployment inflows and outflows in fourteen OECD countries, with a view to analyze sources of unemployment fluctuations over the business cycle and determine whether they differ across countries. Choi et al. [2015] use data for the U.S. to study how worker flows shape the rates of unemployment and labor force participation over the life cycle. Similar to Choi et al. [2015] (and Cajner et al. [2022] in a related and more recent paper), we extract nonparametrically the transition rates between employment, unemployment and nonparticipation for each age between 16 and 65 years.[4] Our focus is then to understand how these age profiles account for differences across countries in aggregate (steady-state) employment. To this end, we implement a calculation based on the Shapley value, which is a new approach to decomposing employment differences into the contribution of specific workers flows. This decomposition can be applied to any number of countries as well as extended to an arbitrary number of labor market states.

As mentioned in the opening paragraph, the facts that we emphasize are only partially incorporated into studies that develop a life cycle version of the DMP model. Chéron et al. [2011, 2013] is a landmark study for this line of research, offering an in-depth analysis of the labor market consequences of the 'horizon effect'. Several follow-up studies, for instance Gorry [2013], Esteban-Pretel and Fujimoto [2014], or Menzio et al. [2016], have developed variants of the DMP model with a 'horizon effect' to analyze the age profile of worker flows and the implications for labor market policies. However, these studies typically abstract from labor force participation. Lalé [2018] develops a similar model but allows for decisions along the participation margin. His focus, however, is on only one end of the age spectrum (older workers). One notable exception is a recent paper by Goensch et al. [2021]. Their analysis is conducted within the directed search model of Menzio et al. [2016], which they extend to include decisions along the labor force participation. They focus on analyzing the effects of unemployment insurance reforms in the U.S. labor market.[5]

There are also a number of studies that analyze a three state – i.e., with employment, unemployment and nonparticipation – DMP model, but without the life cycle component. Early references include Garibaldi and Wasmer [2005] and Pries and Rogerson [2009]. Krusell et al. [2011, 2017] extend this class of model to an incomplete markets setting, but they do so in a context with exogenous labor market frictions. In an interesting study related to ours, Cajner et al. [2022] develop an extensive life cycle version of the model of Krusell et al. [2011]. However, the job offer arrival rates are also exogenous in Cajner et al. [2022]'s model, and the authors let these rates be age-specific to flexibly match the life cycle profiles of worker flows. In contrast, our model replicates the life-cycle profile of worker transition rates – and matches their contribution to cross-country differences in aggregate employment – with age-independent parameters, and job offer arrival rates are determined by the endogenous job creation condition of the standard DMP model. This provides us with a rich environment to run counterfactual analyses of labor market policies.

Roadmap. The paper is organized as follows. Section 2 introduces the data, describes the measurement framework briefly and presents our main empirical findings. A full description of the measurement framework is provided in the appendix. Section 3 presents our theoretical

[4]See, also, Ward-Warmedinger and Macchiarelli [2014] for empirical evidence on worker flows by 10-years age groups in several E.U. countries.

[5]Kitao et al. [2017] develop a rich quantitative life cycle model with labor market frictions to analyze differences in aggregate employment performances between the United States and Europe. They consider labor market frictions as in the search-island model of Lucas and Prescott [1974], which is different from the search-matching process embedded in our model. Also, they do not separate out unemployment from nonparticipation.

model. The calibration is carried out in Section 4, and the quantitative results based on the calibrated model are discussed in Section 6. Section 7 concludes.

2 Data, measurement and empirical findings

This section presents our data and measurement framework. We keep the presentation purposely short and defer the details to Appendix A. The section then presents our main empirical findings.

2.1 Data sources

We use microdata from the Statistics on Income and Living Conditions (EU-SILC) administered by Eurostat. The EU-SILC is an annual survey that collects comparable cross-sectional and longitudinal data on households in multiple countries. The dataset is particularly well suited for our study as it contains the monthly labor force status (employment, unemployment, nonparticipation) of individuals living in the following countries: Austria, Belgium, Bulgaria, Croatia, the Czech republic, Cyprus, Denmark, Estonia, Finland, France, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Norway, Poland, Portugal, Romania, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, and the United Kingdom. Information about monthly labor force statuses are collected via a retrospective calendar.[6] The EU-SILC begins in 2004, and for most countries our sample covers the period 2004-2019.[7] Since the longitudinal data for Germany begins only in 2018, we complement EU-SILC with the 2003-2015 waves of the German Socio-Economic Panel (GSOP). Our final sample has a total of 6,870,510 individual-year observations corresponding to 2,207,721 individuals.

2.2 Measurement framework

Our goal is to measure transition probabilities across three labor force statuses: employment (E), unemployment (U) and nonparticipation (N). Our measurement approach proceeds in several consecutive steps.

Measurement error. Measurement error is a potentially important concern, especially for flows between unemployment and nonparticipation. To address this issue, we develop an approach in the spirit of Elsby et al. [2015]'s de-NUN-ification procedure, and subsequently treat our data as being quarterly instead of monthly. Suppose for instance that we look at data from January (month 1) to June (month 6) for individual i. We define i's labor force status during the first quarter as her labor force status in February (month 2). Likewise, her status in the second quarter is taken to be that in May (month 5). De-NUN-ification means that if we

[6]There is evidence of "recall bias" affecting the retrospective calendars of some labor force surveys; see Hairault et al. [2015] and the references therein. We discuss this issue further below in Subsection 2.2.

[7]Not all countries started the survey in 2004, and sample size varies across countries, ranging from 19,829 individuals in Iceland to 234,286 individuals in Italy. Table A1 in the Appendix provides the time span and sample size for each country as well as some basic descriptive statistics.

observe the sequence NUN within the first (second) quarter, then we recode i's labor status in month 2 (month 5) as N. We treat the sequence UNU in the same way, by recoding i's labor status in month 2 (or 5, if looking at the second quarter) into U. This procedure, which identifies NUN and UNU as suspicious and replaces them with more plausible outcomes, leaves the stocks and flows roughly unchanged in levels and increases the precision of our estimates.

The other concern related to measurement error is "recall bias", as our data come from retrospective calendars contained in the EU-SILC. Approaches that have been proposed in the literature to address recall bias often rely on sophisticated statistical models of measurement errors, such as latent-variable models of the "true" labor force status of individuals (e.g., Magnac and Visser [1999], Feng and Hu [2013]) Using this type of models to check whether our data suffers from recall bias is very costly and somewhat beyond the scope of our study. What we can do instead is compare our estimates based on the EU-SILC with estimates obtained from other data sources that do not rely on retrospective calendar. We do so using the national labor force survey data of France, the United Kingdom, and Switzerland. In Appendix XX, we show that the two data sources deliver estimates that are virtually the same. This suggests that the retrospective calendar of the EU-SILC does not suffer from large recall biases.

Measuring transition probabilities. To calculate stocks and flows for each country, we proceed as follows. Letting $s_{i,a,t}$ denote the indicator function that takes the value of 1 if individual i's labor force status is $s \in \{E, U, N\}$ in period t, when i's age is a, and denoting by w_i the relevant (cross-sectional) survey weight of individual i, we calculate

$$S_{a,t} = \sum_i w_i s_{i,a,t}. \tag{1}$$

$S_{a,t}$ is the stock (or count) of individuals of age a in period t whose labor force status is s. Likewise, we construct $F^{ss'}_{a,t}$, worker flows from labor force status s to status s' at age a in period t, based on age-specific individual indicator function $f^{ss'}_{i,a,t}$ that takes the value of 1 if individual i's labor force status is $s \in \{E, U, N\}$ in period t and $s' \in \{E, U, N\}$, $s \neq s'$, in period $t+1$, and using the relevant (longitudinal) survey weights.[8] Further, in order to increase the precision of our calculations, we use three-year bins centered on each age a and period t. For instance, to calculate $S_{30,t}$, we pool data on individuals aged 29, 30 and 31 in period t. We proceed in the same way with respect to t, i.e. we pool data from $t-1$, t and $t+1$ to compute the period-t stocks and flows statistics. Last, by taking the ratio between flows and stocks data, we obtain estimates of quarterly transition probabilities across employment, unemployment and nonparticipation, $P^{ss'}_{a,t} = \frac{F^{ss'}_{a,t}}{S_{a,t}}$.

Life-cycle profiles. Next, we extract the life-cycle profile of transition probabilities, meaning we remove the time effects (business cycle fluctuations, etc.) contained in the $P^{ss'}_{a,t}$'s. To this

[8] In the EU-SILC, we do not have longitudinal weights tailored to our empirical exercise. Therefore we take the average of an individual's cross-sectional weights to construct longitudinal weights. The other datasets we use provide longitudinal in addition to cross-sectional weights. In particular, for France and the United Kingdom, we compare the flows that we construct based on the longitudinal weights with those based on weights provided in the microdata of the French and U.K. labor force surveys. We find no significant differences.

end, we use a non-parametric approach. We run the following regressions:

$$P_{a,t}^{ss'} = p_a^{ss'}\mathbf{D_a} + \psi_t\mathbf{D_t} + \varepsilon_{a,t}, \tag{2}$$

for each $P_{a,t}^{ss'}$, where $\mathbf{D_a}$ ($\mathbf{D_t}$) is a full set of age (time) dummies and $\varepsilon_{a,t}$ is the residual of the regression. Then, the life-cycle profile of the transition probability from labor force status s to status s' corresponds to the coefficients $p_a^{ss'}$ on the age dummies, which we normalize using the arithmetic mean of the coefficients on the time dummies, the ψ_t's.

Time aggregation. In the next step, we clear the life-cycle transition probabilities $p_a^{ss'}$ from time aggregation bias using the continuous-time adjustment procedure developed by Shimer [2012]. For each country, we then store the time-aggregation adjusted, age-a quarterly transition probabilities in a matrix denoted as Γ_a:

$$\Gamma_a = \begin{bmatrix} p_a^{EE} & p_a^{EU} & p_a^{EN} \\ p_a^{UE} & p_a^{UU} & p_a^{UN} \\ p_a^{NE} & p_a^{NU} & p_a^{NN} \end{bmatrix}. \tag{3}$$

Initial conditions. While transition probabilities are our main object of interest, we are ultimately interested in recovering statistics such as labor force participation and employment rates. The collection of matrices $(\Gamma_a)_{a=16}^{65}$ are necessary but not sufficient for this purpose: we need what we call 'initial conditions', that is to say a distribution of workers across E, U, N at age $a = 16$. Denoting such a distribution as $\begin{bmatrix} E & U & N \end{bmatrix}_{16}'$, stocks for workers in any higher age group, $a > 16$, can be calculated using:

$$\begin{bmatrix} E \\ U \\ N \end{bmatrix}_a = \prod_{\tau=16}^{a-1} \left(\Gamma_\tau'\right)^4 \begin{bmatrix} E \\ U \\ N \end{bmatrix}_{16}. \tag{4}$$

Thus, for each country we retrieve initial conditions by searching the vector $\begin{bmatrix} E & U & N \end{bmatrix}_{16}'$ that maximizes the fit between the employment rates implied by Equation (4) and the actual life-cycle employment rates.[9,10] As will be shown in the next section, we obtain a very good fit in all instances, allowing us to put the focus on transition probabilities.

2.3 Empirical findings

To set the stage for our empirical investigation, we display data derived from our empirical setup for France, Germany, Italy, Spain, and the U.K. – the 'big five' of Europe. We start with the life-cycle employment rates, both the Markov-implied (i.e., implied by the initial conditions

[9] We use the simplex Nelder-Mead algorithm to find the vector of initial conditions.

[10] Results are very similar if we compute $\begin{bmatrix} E & U & N \end{bmatrix}_{16}'$ by targeting life-cycle labor force participation instead of the employment rates.

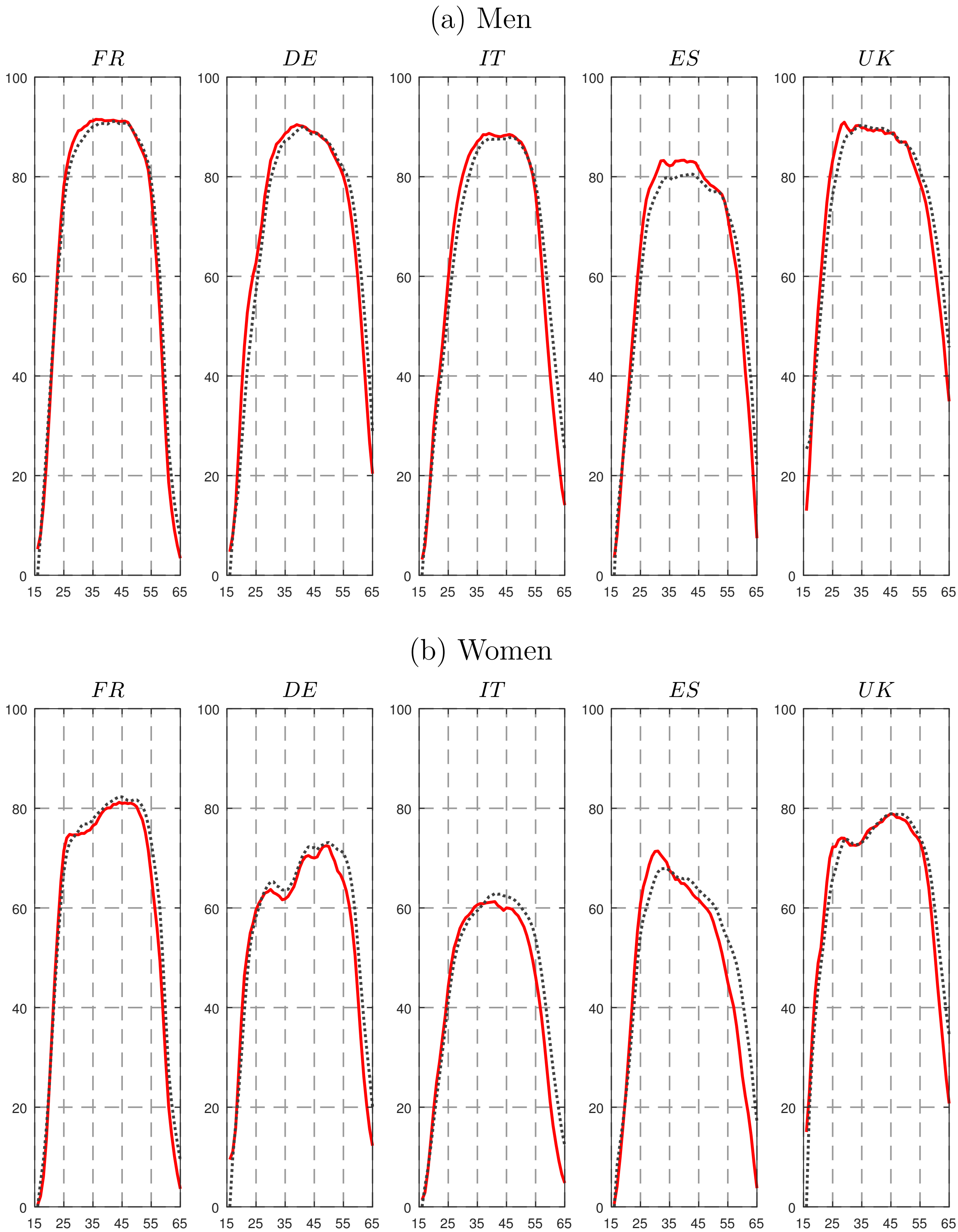


Figure 2: Actual and Markov-implied employment rates: Men (top) and women (bottom)

NOTE: The figure shows the employment rates of men (top) and women (bottom) in France (FR), Germany (DE), Italy (IT), Spain (ES), and the United Kingdom (UK). The dotted lines are the actual employment rates while the solid lines are the Markov-implied (i.e., implied by Equation (4)) employment rates.

and transition probabilities in Equation (4)) and actual rates.[11] They are displayed in Figure 2. The Markov chain model does very well in capturing the patterns of the actual employment rates, including the hump in female employment around ages 25-40 in France, Germany, and the U.K. This holds true for all countries in our sample: in fact, the R-squared of the regression of the dotted line against the solid line is always above 95 percent.

Next, Figures 3a and 3b portray life-cycle transition profiles of male and female workers in France, Germany, Italy, Spain, and the U.K. Loosely speaking, transition probabilities display substantial variations over the working life of individuals. Separation rates, as measured by EU and EN transitions, are high when workers are in their 20s. Then they tend to fall rapidly, but with transitions from E to N that jump up again towards the end of the working life, when workers move into retirement. The effect of retirement is also discernible in transitions from U to N: they are relatively flat throughout the working life and increase substantially after age 55. The shape of the job-finding rates underlying UE and NE transitions is also worthy of attention. Like separation rates, job-finding rates are higher among younger individuals. But they are also more persistent, as they remain well above zero until workers get into their 50s. Last, NU transitions reflect the fact that prime-age workers tend to search for jobs more often from within unemployment rather than nonparticipation. These qualitative patterns are also present in data for the other countries of our sample. Quantitatively, there are substantial differences across countries. We quantify the impact of these differences below.

We now move on to our empirical findings, which we organize around three sets of main results. They follow naturally from using the data to decompose cross-country differences in aggregate employment. Denote by E^c the aggregate employment rate of country c, and let E^r refer to some reference employment rate (say, the average of employment rates across the countries analyzed). The employment rate of country c is given by

$$E^c = \sum_a W_a^c E_a^c, \tag{5}$$

where W_a^c is the population weight of workers at age a and E_a^c denotes the employment rate of these workers. In the sequel, we refer to E_a^c as the age, or life-cycle, profile of employment in country c. We are ultimately interested in the difference $E^c - E^r$.

2.3.1 Demographics vs. initial conditions vs. transition probabilities

Consider replacing country c's initial conditions (i.e., country c's distribution across E, U, N at $a = 16$) with r's initial conditions, while using c's transition probabilities (i.e., country c's Γ_a's) to calculate a counter-factual employment profile, denoted as $\widetilde{E_a^c}$. This profile interests us because it puts the focus on the role of transition probabilities in country c. We have:

$$E_a^c - E_a^r = E_a^c - \widetilde{E_a^c} + \widetilde{E_a^c} - E_a^r. \tag{6}$$

[11]To calculate the actual employment rates, we extracted the life-cycle profile of stocks (the $S_{a,t}$'s defined in Equation (1)) using regression (2). We also use the life-cycle profile of stocks to calculate the weight of workers in age group a in the overall population of working age, denoted as W_a below.

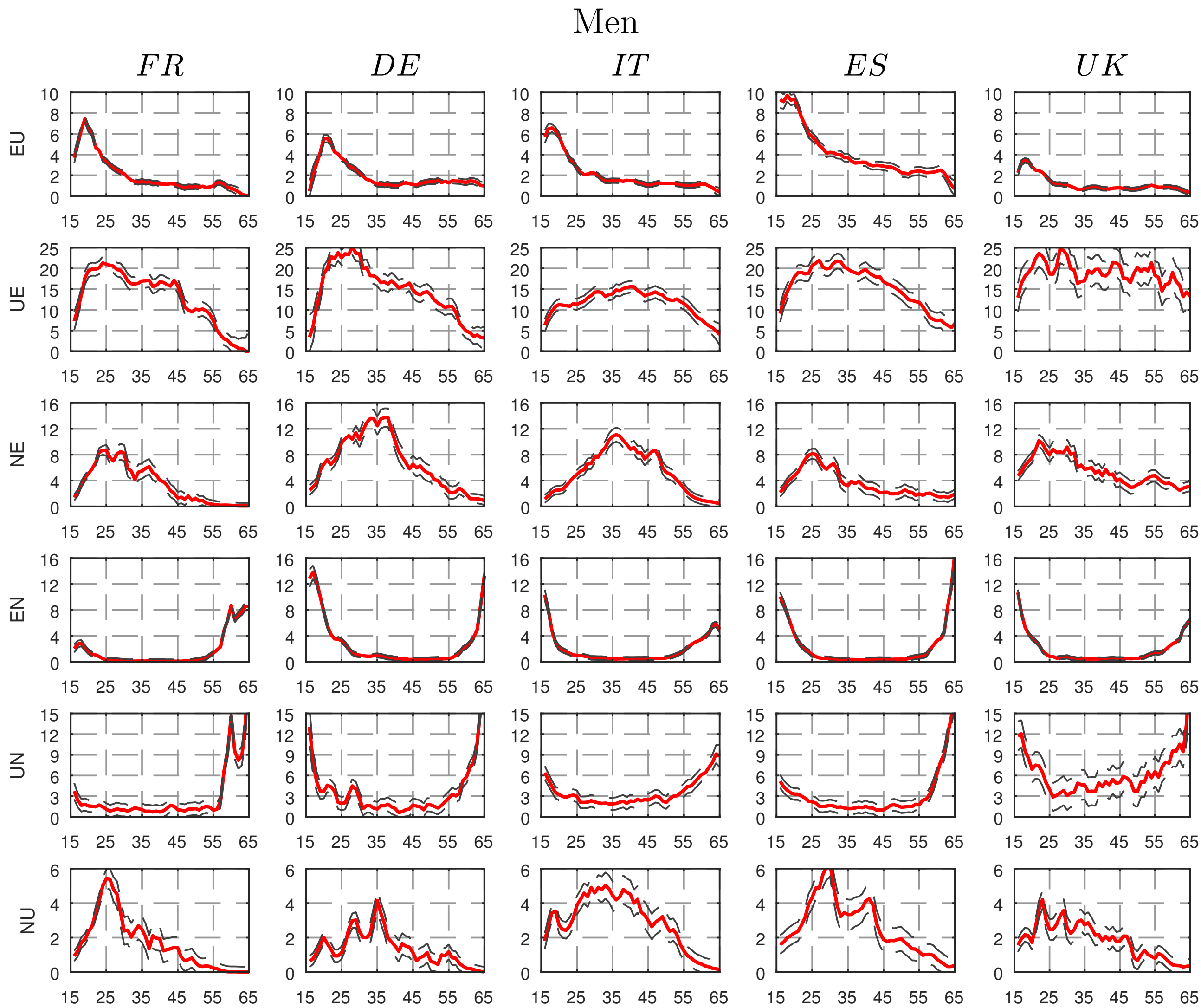


Figure 3a: Transition probabilities: Men

NOTE: The plots show quarterly transition probabilities of workers between employment (E), unemployment (U) and nonparticipation (N) in France (FR), Germany (DE), Italy (IT), Spain (ES), and the United Kingdom (UK). Figures are expressed in percentage points. The dashed lines are 95 percent confidence intervals.

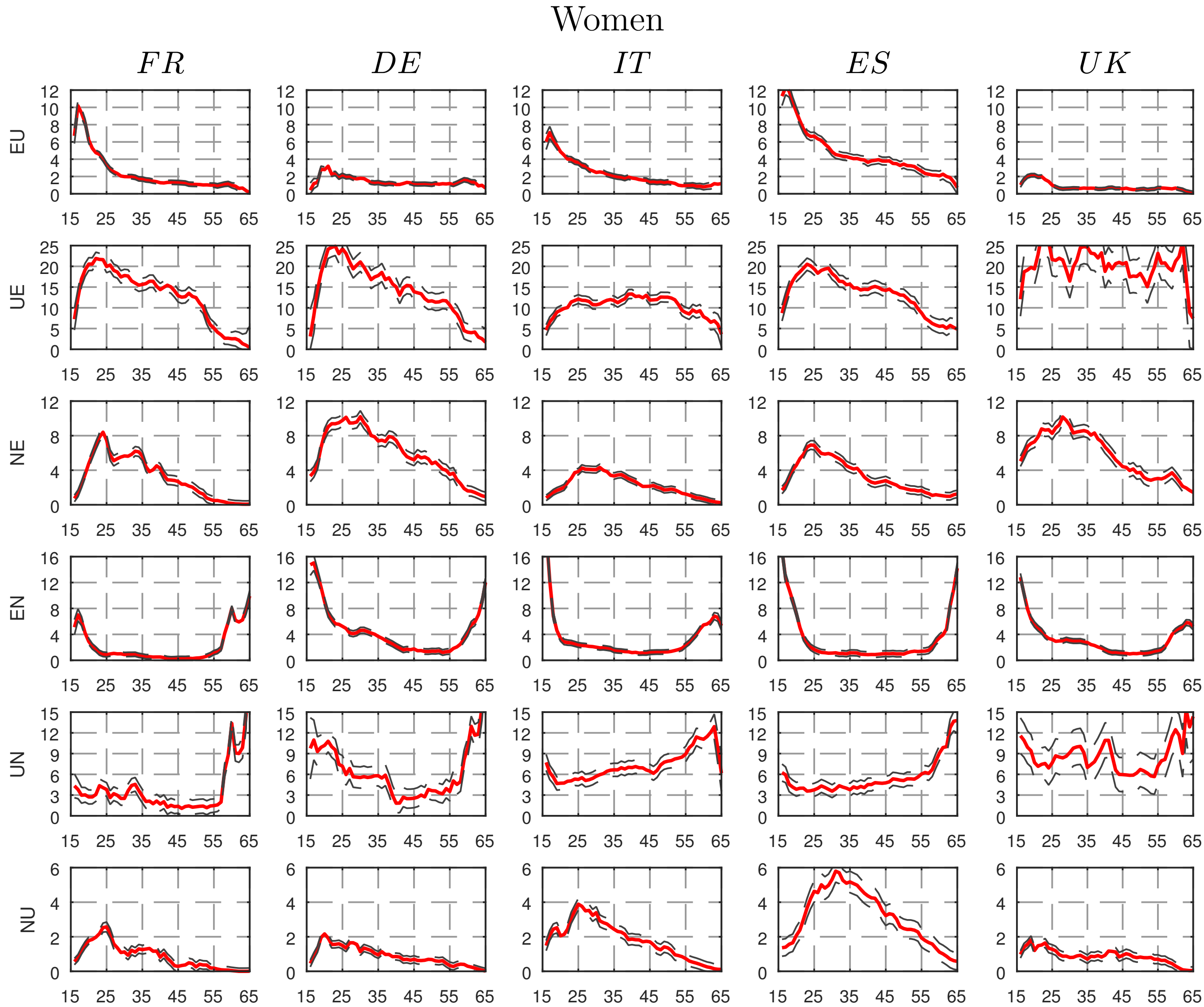


Figure 3b: Transition probabilities: Women

NOTE: The plots show quarterly transition probabilities of workers between employment (E), unemployment (U) and nonparticipation (N) in France (FR), Germany (DE), Italy (IT), Spain (ES), and the United Kingdom (UK). Figures are expressed in percentage points. The dashed lines are 95 percent confidence intervals.

Table 1: Decomposition of aggregate employment differences based on Equation (7)

	Demographics	**Initial conditions**	**Transition probabilities**
		'Big five' of Europe	
Men:	3.59	3.01	93.40
Women:	-3.71	-1.40	105.11
		All 31 European countries	
Men:	3.88	1.40	94.72
Women:	0.54	-0.36	99.82

Notes: The entries in the table are the contributions (expressed in percent) of demographics, initial conditions, and transition probabilities, to the cross-country variance of employment (Equation (7)).

To aggregate up, we can choose to apply either the population weights W_a^c or W_a^r to Equation (6). This provides us with the following decomposition of the aggregate employment gap between countries c and r:

$$E^c - E^r = \underbrace{\sum_a \left(W_a^c - W_a^r\right) E_a^c}_{\text{demographics}} + \underbrace{\sum_a W_a^r \left(E_a^c - \widetilde{E_a^c}\right)}_{\text{initial conditions}} + \underbrace{\sum_a W_a^r \left(\widetilde{E_a^c} - E_a^r\right)}_{\text{transition probabilities}}. \tag{7}$$

The first term measures the role of demographics in explaining employment differences between c and r. The second term isolates the role of initial conditions, as this is the only difference between the two age profiles E_a^c and $\widetilde{E_a^c}$. In the third term, initial conditions are the same (that is, individuals at age 16 start from r's initial conditions) and differences are fully explained by the transition probabilities of country c relative to r.

We use Equation (7) to run a variance decomposition and establish the first of our main empirical result: differences in aggregate employment are overwhelmingly explained by differences in transition probabilities. As reported in Table 1, transition probabilities explain 93 to 95 percent of the dispersion of aggregate employment rates for men. For women the variance contribution is 100 to 105 percent. Based on this, in the rest of this section we focus on understanding variation in the last summand of Equation (7) which measures the employment gap net of the effects of different demographics and initial conditions.

Before closing this subsection, we note that the results in Table 1 mask some region-specific patterns that may be of interest in their own rights. One such pattern is the larger role of demographics (presumably due to migration) in the Baltic states, and to a lesser extent in Eastern Europe. We refer the interested reader to Appendix XX for further details.

2.3.2 Contribution of each transition probability

Next, we turn to the issue of isolating the contribution of each transition probability to net aggregate employment differences (the last summand of Equation (7)). Let $\widetilde{E_a^c}^{p_1,p_2,\ldots}$ denote the life-cycle profile of employment in country c starting from r's initial condition *and* using r's transition probabilities $p_1, p_2, \ldots$ while the remaining probabilities of the counterfactual transition matrices ($\widetilde{\Gamma}_a$'s) are those of country c.[12] Using these counterfactuals, one can decompose the difference in life-cycle employment profiles between c and r as:

$$\widetilde{E_a^c} - E_a^r = \underbrace{\widetilde{E_a^c} - \widetilde{E_a^c}^{EU}}_{EU} + \underbrace{\widetilde{E_a^c}^{EU} - \widetilde{E_a^c}^{EU,EN}}_{EN} + \underbrace{\widetilde{E_a^c}^{EU,EN} - \widetilde{E_a^c}^{EU,EN,UE}}_{UE} \tag{8}$$

$$+ \underbrace{\widetilde{E_a^c}^{EU,EN,UE} - \widetilde{E_a^c}^{EU,EN,UE,UN}}_{UN} + \underbrace{\widetilde{E_a^c}^{EU,EN,UE,UN} - \widetilde{E_a^c}^{EU,EN,UE,UN,NE}}_{NE} + \underbrace{\widetilde{E_a^c}^{EU,EN,UE,UN,NE} - E_a^r}_{NU}.$$

It is important to note that the decomposition of $\widetilde{E_a^c} - E_a^r$ along the lines of Equation (8) is path-dependent and thus not unique. In fact, there are $6! = 720$ ways of writing the decomposition of $\widetilde{E_a^c} - E_a^r$, and $2^{6-1} = 32$ ways of measuring the contribution of a given transition probability based on these decompositions. Since the employment rate depends on the transition probabilities in a non-linear fashion, the different approaches to decomposing $\widetilde{E_a^c} - E_a^r$ might lead to different results.

We use the Shapley value to circumvent this issue. We compute the marginal contribution of each transition probability to the aggregate employment gap in all 720 decompositions, and then average these contributions out. By doing so, we obtain for each transition probability a single number measuring its contribution to employment differences.

Table 2 reports outcomes of these calculations. The figures for men form the basis of our second main empirical result: employment separations towards unemployment accounts for the lion's share of the cross-country variance in aggregate male employment. When looking across all 31 countries of our sample, the variance contributions of EU transitions is about one half. It rises to three quarters when looking at the 'big five' of Europe, and to over 85 percent if we focus on prime-age male employment. Strikingly, transitions in the reverse direction (UE) explain less than 30 percent of the variance across all 31 countries, and play almost no role in the 'big five'. Also of note is that labor force participation plays a non-negligible role for male workers. Adding up the variance contributions of NE and EN transitions shows that nonparticipation explains between 25 and 30 percent of the aggregate employment gap for men.

Our third main empirical result concerns the cross-country variance in aggregate female employment: at least half of it is explained by labor force participation, and chiefly by transitions from nonparticipation to employment (NE). The latter result holds true in the larger sample of countries, where NE explains 65 percent of the variance for female employment at large. Its role is slightly lower in the 'big five', while on the other hand EN plays a larger explanatory role in this set of countries. Related, in both panels of Table 2 for women, the sum of variance contributions from NE and EN is at least as large as the sum of variance contributions from UE and EU. This underscores the importance of using a three-state model to analyze cross-country differences in female employment.

It is useful to ask how the above sets of results change when looking at the data country

[12]We keep the $\widetilde{\Gamma}_a$'s well defined (i.e., a stochastic matrix) by adjusting the probabilities of staying in each labor market status (EE, UU, NN).

Table 2: Decomposition measuring the role of each transition probability

		EU	EN	UE	UN	NE	NU
				'Big five' of Europe			
Men:	**16-65**	74.76	1.79	14.45	-12.99	27.67	-5.68
	25-54	86.36	16.16	-0.97	-5.41	10.02	-6.17
Women:	**16-65**	34.73	12.19	15.03	4.29	46.17	-12.41
	25-54	35.68	24.79	12.77	5.89	34.42	-13.56
				All 31 European countries			
Men:	**16-65**	51.43	7.21	28.97	-7.64	23.02	-3.00
	25-54	53.18	18.93	24.27	-5.48	12.07	-2.97
Women:	**16-65**	21.85	-6.78	28.08	-5.39	65.44	-3.20
	25-54	26.42	2.53	25.31	-3.87	51.98	-2.37

Notes: The entries in the table are the contributions (expressed in percent) of each transition probability to the cross-country variance of employment. Employment refers to the last summand of Equation (7), which nets out the effects of different demographics and initial conditions.

by country. The answer is: not much. For men, in most countries, EU transitions remain the main driver of the aggregate employment gap relative to the average of the sample. The main exception are countries of Eastern Europe, where NE plays a predominant role (Table A3a in the appendix). For women, the patterns described above, i.e. the major role played by the labor force participation margin, continue to hold on a country-by-country basis (see Appendix Table A3b). In sum, the empirical analysis sheds light on the importance of job separations and labor force participation when accounting for differences in employment rates at both the aggregate level and over the life-cycle.

3 The model

To delve further into the relationship between flows across the three labor market states (employment, unemployment, nonparticipation), the life cycle, and labor market institutions, we set up a macro-search model that can be calibrated and is usable for counterfactual analysis. The model features a life-cycle (age) dimension with a deterministic retirement horizon; permanent heterogeneity in match quality and match-specific productivity shocks; endogenous search intensity; and discrete participation choices (unemployment vs. nonparticipation).

Moreover, we model labor market institutions that are most often scrutinized when looking at cross-country differences in labor market outcomes, namely unemployment benefits (UI insurance), employment protection legislation (EPL), and taxes (under the form of value-added taxes and social-security contributions).

3.1 Economic environment

Time is discrete and runs forever. We will confine ourselves to stationary equilibria so we do not introduce any time subscript. We use a prime ($'$) to denote the one-period-ahead value of variables. We consider an economy with search frictions, populated by workers and firms, with access to a production technology of a final consumption good (the numéraire).

Workers. On one side of the market, there is a unit continuum of risk-neutral workers living for $T > 0$ periods. A worker's age is denoted $\tau = 0, 1, ..., T$. At age T, the worker retires (dies) and is replaced by a newborn worker with age $\tau = 0$: generations overlap and entries equal exits to keep the population measure at a constant level. The population is composed of men and women. For the sake of clarity, we abstract from this distinction in the model presentation of this Section, but it is explicitly reintroduced in the calibration (Section 4) and quantitative analysis (Section 6) sections. It is straightforward but cumbersome to extend the model to account for such a distinction; we leave a presentation of the full model in a supplementary appendix.

Workers discount the future at rate $\beta^{-1} - 1$. They derive utility from both consumption and leisure. Workers can be in three distinct labor-market states: employment, unemployment, or nonparticipation, with associated population denoted by $\mathcal{L}_e$, $\mathcal{L}_u$ and $\mathcal{L}_n$, respectively. The two latter states are referred to as out-of-work or nonemployment states. All workers are born in nonparticipation.

In each period, workers are endowed with one unit of time. Employed workers allocate their entire time endowment to selling labor to firms against wage payments denominated in units of the final consumption good (the numéraire). There is no saving, and workers' income is entirely consumed in each period. Nonemployed workers allocate their time to home production and searching for a job. Specifically, they allocate a fraction $s \in [0, 1]$ of their time endowment to search in each period. This comes at a cost $c_u(s)$ when the worker is unemployed, and $c_n(s)$ when the worker is employed, where $c_u : [0, 1] \to \mathbb{R}_+$ and $c_n : [0, 1] \to \mathbb{R}_+$ are search costs functions that are specific to the labor market status. We assume the functional forms

$$c_j(s) = \frac{\chi_j^{\zeta}}{1+\zeta}\, s^{1+\zeta}, \tag{9}$$

for all $s \in [0, 1]$, $j \in \{n, u\}$, with the parameters $\chi_n, \chi_u, \zeta > 0$. Search is more efficient in the unemployment state, in the sense that $\chi_u \leq \chi_n$: as it will become clear in what follows, the probability of matching per search-cost unit is higher in unemployment. This assumption traduces differences in the search technology across labor market states.[13]

A nonemployed worker produces at home (and consumes) a constant amount equivalent to $y_o > 0$ units of the final good in each period, regardless of their state and the time dedicated to search. Moreover, unemployed workers receive unemployment benefits, as discussed in the following. At the end of each period, a nonemployed agent chooses between unemployment or

[13] Alternatively, one could assume a cost function independent of the state, with state-specific matching efficiency.

nonparticipation for the following period. More specifically, at the end of each period, the agent draws random, transitory i.i.d. and non-observable state variables ν_u' and ν_n', with c.d.f. denoted by H. For the sake of analytical and computational tractability, we assume that ν_u and ν_n follow standard extreme value type-I distributions. These random variables are interpreted as non-monetary transitory utility shocks associated with being in unemployment or nonparticipation. At the beginning of each period, the labor-market state is predetermined; an agent remaining nonemployed must wait until the end of the period to draw new utility shocks and reallocate across nonparticipation and unemployment.

An agent entering unemployment from employment and nonparticipation must pay a fixed entry sunk cost $\overline{c}_{eu} \geq 0$ or $\overline{c}_{nu} \geq 0$, depending on the origin state. This entry cost allows the agent to activate the unemployment search technology, assumed to be more efficient than in nonparticipation. These are interpreted as set-up costs for gaining access to the unemployment-state search technology. Lastly, the unemployed worker pays a constant search cost $\overline{c}_u \geq 0$ per period to operate the unemployment search technology: the higher efficiency of the unemployment search technology comes at fixed operating and set-up costs. Lastly, we denote by $\bar{s}_n$ and $\bar{s}_u$ the aggregate search effort of the nonparticipants and the unemployed individuals, respectively.

Firms. On the other side of the market, there is a continuum of risk-neutral, infinitely-lived firms with a discount rate $\beta^{-1} - 1$. To produce, a firm must post a vacancy at a per-period cost of c_v to attract a worker. The output of a match between a worker and a firm is $y(x, z)$, where $y : \mathcal{X} \times \mathcal{Z} \to \mathbb{R}_+$. The component $x \in \mathcal{X} \subset \mathbb{R}_+$ is called the permanent *match quality*, or more simply, the match quality, drawn at the beginning of the match in a distribution with c.d.f. G_x and support $\mathcal{X}$. This is assumed constant throughout the duration of the job. Match quality is assumed to be an experience good, unobserved upon matching but eventually discovered by agents throughout their employment relationship. The quality of a match is discovered with probability α in each period subsequent to matching. Prior to observing the true match quality, the agents form beliefs for the expected output that are consistent with the distribution G_x: expectations for the match output are taken over the distribution G_x. Finally, worker-firm matches are subject to idiosyncratic productivity shocks (independent of x) materialized by $z \in \mathcal{Z}$. New matches start at a fixed value $z = z_0 \in \mathcal{Z} \subset \mathbb{R}_+$, and subsequent values evolve following a first-order Markov process with transition function $G_z(.|z)$.

Search and matching. The labor market features search frictions, and search is random. The number of contacts between nonemployed workers and firms with a vacancy in each period is $m(\mathcal{L}_n^* + \mathcal{L}_u^*, \mathcal{V})$, where $\mathcal{L}_n^* \equiv \bar{s}_n \mathcal{L}_n$ and $\mathcal{L}_u^* \equiv \bar{s}_u \mathcal{L}_u$ represent the effective measures of job seekers in nonparticipation and unemployment, determined by the aggregate search intensity and the number of nonemployed agents; $\mathcal{V}$ is the vacancy rate. The function m is Cobb-Douglas with $m(\mathcal{L}_n^* + \mathcal{L}_u^*, \mathcal{V}) = A(\mathcal{L}_n^* + \mathcal{L}_u^*)^\eta \mathcal{V}^{1-\eta}$, with matching efficiency $A > 0$ and elasticity with respect to the effective mass of job seekers $\eta \in (0, 1)$. For future reference, a worker's job-finding probability per search intensity unit is $p(\theta) \equiv m(1, \theta)$, where $\theta \equiv \mathcal{V}/(\mathcal{L}_n^* + \mathcal{L}_u^*)$ is the labor-market tightness, defined as the ratio of the number of vacant jobs to the effective mass of job seekers.

The job-filling probability of a vacancy is $q(\theta) \equiv {}^{p(\theta)}/_{\theta}$. Search frictions imply employment rents. As is standard in the literature, we assume that these rents are split through Nash bargaining; the workers' relative bargaining is $\gamma \in (0, 1)$.

Labor market institutions. We consider three types of labor-market institutions: unemployment insurance (UI) benefits, employment protection legislation (EPL), and labor taxes.

First, we model a UI system with work-history and active job-search eligibility conditions, as typically seen in actual legislation. Specifically, we distinguish between low ($b_0 > 0$) and high ($b_1 > b_0$) UI benefits. We also distinguish between conditions for eligibility and the provision of UI benefits. On the one hand, all workers are *eligible* to receive these UI benefits (either low or high), but eligibility for high UI benefits depends on some work-history conditions (shortly described). On the other hand, *provision* of UI benefits is conditional on choosing the *unemployment* state over nonparticipation. This reflects job-search activity requirements mandated by actual legislation for UI eligibility.

The work-history conditions are as follows. Eligibility for high UI benefits b_1 is granted to any employed worker experiencing a separation into nonemployment. When the individual is nonemployed, eligibility exhausts with probability $\overline{\mu}_o$. After exhaustion, an individual choosing the unemployment state will receive low UI benefits b_0 (i.e., is eligible to receive low UI benefits). After exhaustion, regaining eligibility for high UI benefits requires reentering into employment. We assume that a newborn worker is only eligible for low UI benefits.

Second, we model a two-tier EPL system, reflecting the job seniority dependence on the stringency of unemployment protection and the large incidence of temporary jobs, as seen in European countries. Jobs are subject to firing costs F_i, $i = 0, 1$, paid by employers upon match termination. We distinguish between a low and high firing-cost regime indexed by $i = 0, 1$, with $0 \leq F_0 \leq F_1$. Any newly formed job is subject to the low firing cost regime with firing costs F_0. With probability $\overline{\mu}_e$, the job becomes subject to high firing costs F_1.

Third, we consider proportional value-added and social-security contribution taxes. The value-added tax is collected on a match output, and the associated tax rate is $\phi \in (0, 1)$. The social security tax is a fraction $\psi \in (0, 1)$ of the period wage rate. For simplicity, we assume statutory tax incidence on the worker, but we calibrate ψ so that the tax wedge is consistent with rates of employee and employer contributions seen in the data.

Assuming stochastic durations for UI and EPL regimes allows us to economize on the model state space. To fix ideas, one should think about the high UI regime and the low EPL regime lasting for about one year, an order of magnitude that we believe reflects existing schemes in prevailing legislation. In sum, the parameters b_0 and b_1 are proxies for the generosity of UI systems, whereas F_0 and F_1 proxy the stringency of EPL. Note, lastly, that firing costs and taxes are assumed to be deadweight losses and that we abstract from the government budget.

Timing. First, recall that a newborn individual ($\tau = 0$) is born in nonparticipation. At the end of age $\tau = 0$, the individual chooses between staying in nonparticipation and transiting into unemployment for the following period ($\tau = 1$).

In addition, the sequence of events and actions for a nonemployed agent with age $\tau =$

$1, ..., T-1$ within a period t is the following. (i) At the beginning of age t and conditional on the labor-force status, the agent receives period utility from home production and possible UI transfers, net of search costs; the agent sets the optimal (i.e., maximizing expected lifetime utility) search intensity; (ii) the age and UI status are updated; (iii) the agent meets a vacancy with probability determined by the labor-market tightness and search intensity predetermined in step (iv) and gets hired if the associated surplus is nonnegative; otherwise, the agent stays nonemployed; (v) The hired worker starts in employment in $t+1$; the agent remaining out of work chooses between nonparticipation and unemployment for the period $t+1$.

For an employed worker, the sequence is the following: (i) at the beginning of t, production and wage payments occur; (ii) the age, EPL status, and match-specific state are updated; (iii) the match continues if the surplus remains positive or is terminated otherwise; (iv) A continuing worker remains employed in $t+1$; a terminated worker goes to nonemployment and chooses the labor-force status for $t+1$.

At age T, an employed or nonemployed individual (i) produces (at home or on the market), collects payments, and (ii) retires at the end of the period. The worker "dies"; equivalently, the worker leaves the labor force forever and receives lifetime utility normalized to zero. A newborn worker of age $\tau = 0$ enters the labor force, replacing the retiring worker. This worker makes a participation decision according to (i) upon entry into the labor market and starts to search for a job at age $\tau = 1$.

3.2 Bellman equations

Worker. We formulate the decision problems of workers using a system of (finite horizon) value functions that can be solved by backward induction. To begin with, let $V_{\tau,n,i}$ and $V_{\tau,u,i}$ represent the value functions of a worker of age τ in nonparticipation and unemployment, respectively, for all $\tau = 1, ..., T$ and all $i = 0, 1$. Let the index i indicates whether this worker is eligible ($i = 1$) or not ($i = 0$) to receive high unemployment benefits b_1.

One must distinguish between a match with revealed and unrevealed quality when valuing the employed worker's lifetime utility. Denote by $\tilde{V}_{\tau,e,i} : \mathcal{Z} \to \mathbb{R}$ the expected lifetime utility value of a worker in a match with unrevealed quality, and by $V_{\tau,e,i} : \mathcal{X} \times \mathcal{Z} \to \mathbb{R}$ the value of a match with revealed quality, for $\tau = 2, ..., T$ and $i = 0, 1$.[14] Here, the index indicates the match's EPL status, with associated firing costs F_i.

Observe that the assumption of Nash Bargaining and flexible wages subject to renegotiation in each period implies that period wage payments (and profits) depend on the current match state and the agents' outside options. These outside options are determined by the worker's UI and job's EPL status and on whether one considers a match in a *hiring stage* (i.e., a new match) or in a *renegotiation stage* (i.e., a continuing match). As such, let $\tilde{V}_{\tau,ne,i} : \{z_0\} \to \mathbb{R}$ and $\tilde{V}_{\tau,ue,i} : \{z_0\} \to \mathbb{R}$, $\tau = 2, ..., T$, $i = 0, 1$, represent the value functions of an individual at the hiring stage, coming from nonparticipation and unemployment, respectively. Here, we use the index i to denote the individual's UI status upon hiring. Recall that a new match starts

[14] An individual cannot be employed before age $\tau = 2$, as $\tau = 0$ (birth) is dedicated to making a participation decision and $\tau = 1$ is dedicated to search accordingly.

with stochastic productivity $z = z_0$ by assumption.

A worker of age τ in nonparticipation has an expected lifetime discounted utility value given by

$$V_{\tau,n,i} = \max_{s\in[0,1]} \Bigg\{ y_o - c_n(s) \\ + \beta \sum_{i'\in\{0,1\}} \mu_o(i'|i) \Big[sp(\theta) \max\big(\tilde{V}_{\tau+1,ne,i'}(z_0),\, \overline{V}_{\tau+1,n,i'} \big) + (1 - sp(\theta))\overline{V}_{\tau+1,n,i'} \Big] \Bigg\}, \tag{10}$$

for all $\tau = 1, ..., T-1$, $i \in \{0,1\}$, where

$$\overline{V}_{\tau+1,n,i'} \equiv \log \Big[\exp\big(V_{\tau+1,n,i'}\big) + \exp\big(V_{\tau+1,u,i'} - \overline{c}_{nu}\big) \Big], \tag{11}$$

for all $i' = 0,1$ and which represents the expected value of remaining nonemployed at the end of period τ, which closed-form expression follows from the assumption of i.i.d. extreme value shocks of type I (Aguirregabiria and Mira [2010]). Note that this value depends on the labor-force status at age τ due to the fixed unemployment entry cost $\overline{c}_{nu}$, which is specific to nonparticipation. Moreover, in expression (10), μ_o denotes the transition function for the UI eligibility state summarized by i, as implied by the stochastic duration parameter $\overline{\mu}_o$.

Hence, the nonparticipating worker chooses search effort to maximize lifetime utility, composed of (i) period home production net of search costs and (ii) the discounted next-period value of nonemployment taken over the conditional distribution of the UI eligibility state. With probability $sp(\theta)$, the worker meets a vacancy and gets the value of a job with unrevealed match quality in the low EPL regime ($i = 0$). With the complement probability, the worker stays in the out-of-work state and obtains the expected value given by (11), determined by optimal participation choices conditional on nonmonetary shocks. As discussed above, leaving nonparticipation for unemployment implies paying the fixed set-up cost $\overline{c}_{nu}$.

Similarly, the value function of an unemployed worker is

$$V_{\tau,u,i} = \max_{s\in[0,1]} \Bigg\{ y_o + b_i - c_u(s) - \overline{c}_u \\ + \beta \sum_{i'\in\{0,1\}} \mu_o(i'|i) \big[sp(\theta) \max(\tilde{V}_{\tau+1,ue,i'}(z_0), \overline{V}_{\tau+1,u,i'}) + (1 - sp(\theta))\overline{V}_{\tau+1,u,i'} \big] \Bigg\}, \tag{12}$$

for all $\tau = 1, ..., T-1$, $i \in \{0,1\}$, and where the value of remaining out of worker at the end of τ is

$$\overline{V}_{\tau+1,u,i'} \equiv \log \Big[\exp\big(V_{\tau+1,n,i'}\big) + \exp\big(V_{\tau+1,u,i'}\big) \Big], \tag{13}$$

for all $i' = 0,1$. This value function is similar to (10) except that an unemployed worker receives unemployment benefits b_i dependent on the UI eligibility status and that there is no cost of reallocation across labor-market states, as seen in the expected maximized value function (13).

The terminal values are given by

$$V_{T,n,i} = y_o \tag{14}$$
$$V_{T,u,i} = y_o + b_i - \overline{c}_u \tag{15}$$

for all $i' = 0, 1$.

It is convenient to focus now on the case of a continuing match taken at the renegotiation stage. The expected discounted utility of a worker employed in a job with unrevealed match quality is

$$\begin{aligned}\tilde{V}_{\tau,e,i}(z) =\ & (1-\psi)\tilde{\omega}_{\tau,i}(z) + \beta \sum_{i' \in \{0,1\}} \mu_e(i'|i) \int \Big\{ (1-\alpha) \max\big(\tilde{V}_{\tau+1,e,i'}(z'), \overline{V}_{\tau+1,e}\big) \\ & + \alpha \int \max\big(V_{\tau+1,e,i'}(x', z'), \overline{V}_{\tau+1,e}\big) dG_x(x') \Big\} dG_z(z'|z) \end{aligned} \tag{16}$$

for all $\tau = 2, ..., T-1$, $i = 0, 1$, and $z \in \mathcal{Z}$. The value of a worker in a job with revealed quality is

$$V_{\tau,e,i}(x, z) = (1-\psi)\omega_{\tau,i}(x, z) + \beta \sum_{i'} \mu_e(i'|i) \int \max\big(V_{\tau+1,e,i'}(x, z'), \overline{V}_{\tau+1,e}\big) dG_z(z'|z), \tag{17}$$

for all $\tau = 2, ..., T-1$, $i = 0, 1$, and $(x, z) \in \mathcal{X} \times \mathcal{Z}$. In (16) and (17), we let

$$\overline{V}_{\tau+1,e} \equiv \log\Big[\exp\big(V_{n,\tau+1,1}\big) + \exp\big(V_{u,\tau+1,1} - \overline{c}_{eu}\big)\Big], \tag{18}$$

for $\tau = 2, ..., T-1$, which represents the expected value of a job separation into nonemployment, similar to the out-of-work values (11) and (13). Note that the latter is independent of the EPL status indexed by i (attached to the match) and that this expectation is taken over out-of-work values associated with UI status with high benefits b_1 ($i = 1$). Indeed, by assumption, the employed worker is always eligible for high UI benefits. Also note that the relevant unemployment entry cost is now $\overline{c}_{eu}$, which is specific to employment as an origin state. Moreover, we denote by $\omega_{\tau,i}(z)$ and $\omega_{\tau,i}(x, z)$ the worker's (pre-tax) wage in these value functions (shortly analyzed).

As such, the unrevealed match-quality value function (16) consists of the current after-tax wage and a discounted expected value, taken over the distribution of next-period possible EPL status i', and stochastic match-specific shocks z'. The expectation also depends on the possible next-period match quality; with probability α, the match quality is revealed, i.e., drawn from the distribution with c.d.f. G_x. The value function (17) has similar form, except that the match quality remains constant once it is revealed to the agents. When the match surplus is negative, termination occurs, and the worker receives utility given by (18).

The terminal values satisfy

$$\tilde{V}_{T,e,i}(z) = (1-\psi)\tilde{\omega}_{T,i}(z); \quad z \in \mathcal{Z} \tag{19}$$
$$V_{T,e,i}(x, z) = (1-\psi)\tilde{\omega}_{T,i}(x, z); \quad x \in \mathcal{X},\ z \in \mathcal{Z}. \tag{20}$$

In addition, observe that the worker's value at the hiring stage (showing up in (10) and (12) and for individuals hired from nonparticipation and unemployment) must satisfy

$$\tilde{V}_{\tau,ne,i}(z) = \tilde{V}_{\tau,e,0}(z) + (1-\psi)(\tilde{\omega}_{\tau,ne,i}(z) - \tilde{\omega}_{\tau,e,0}(z)) \tag{21}$$

$$\tilde{V}_{\tau,ue,i}(z) = \tilde{V}_{\tau,e,0}(z) + (1-\psi)(\tilde{\omega}_{\tau,ue,i}(z) - \tilde{\omega}_{\tau,e,0}(z)), \tag{22}$$

for $\tau = 2, ..., T$, $i = 0, 1$, and $z \in \{z_0\}$; $\tilde{\omega}_{\tau,ne,i}(z)$ and $\tilde{\omega}_{\tau,ne,i}(z)$ represent the wage paid to the worker in the period upon which hiring takes place.

Firm's profits. We now analyze value functions for the expected lifetime profits of a firm with an occupied job (i.e., matched with a worker). We impose from now on a zero profit condition for vacant jobs and let the analysis of the associated equilibrium labor-market tightness to subsection 3.7 that follows. We let $\tilde{\Pi}_{\tau,i} : \mathcal{Z} \to \mathbb{R}$ and $\Pi_{\tau,i} : \mathcal{X} \times \mathcal{Z} \to \mathbb{R}$, $\tau = 2, ..., T$, $i = 0, 1$ be asset continuation values for jobs with unrevealed and revealed quality, respectively, occupied by a worker with age τ and EPL status indexed by i. We also let $\tilde{\Pi}_{\tau,ne,i} : \{z_0\} \to \mathbb{R}$ and $\tilde{\Pi}_{\tau,ue,i} : \{z_0\} \to \mathbb{R}$ be asset values for a job taken at the hiring stage, occupied by a worker coming from nonparticipation and unemployment, respectively.

The asset value of an occupied (continuing) job with unrevealed quality is

$$\begin{aligned}\tilde{\Pi}_{\tau,i}(z) &= (1-\phi)\int y(x',z)dG_x(x') - \tilde{\omega}_{\tau,i}(z) + \beta\sum_{i'}\mu_e(i'|i) \\ &\times \int\left\{(1-\alpha)\max\left(\tilde{\Pi}_{\tau+1,i'}(z'), -F_{i'}\right) + \alpha\int\max\left(\Pi_{\tau+1,i'}(x',z'), -F_{i'}\right)dG_x(x')\right\}dG_z(z'|z);\end{aligned} \tag{23}$$

for all $\tau = 2, .., T-1$, $i = 0, 1$, and $z \in \mathcal{Z}$. For a job with revealed match quality, we have

$$\Pi_{\tau,i}(x,z) = (1-\phi)y(x,z) - \omega_{\tau,i}(x,z) + \beta\sum_{i'}\mu_e(i'|i)\int\max(\Pi_{\tau+1,i'}(x,z'), -F_{i'})dG_z(z'|z), \tag{24}$$

for $\tau = 2, .., T-1$, $i = 0, 1$, and $(x, z) \in \mathcal{X} \times \mathcal{Z}$. These values are symmetric to (16) (17), except that the period return is now composed of the (expected) match output net of taxes and wage payments, and that the employer's outside option appearing in the expectation term depends directly on firing costs F_i.

Note that an unrevealed match-quality job is valued using the expected output taken over the match-quality distribution G_x. The firm's terminal profit values are:

$$\tilde{\Pi}_{T,i}(z) = (1-\phi)\int y(x',z)dG_x(x') - \tilde{\omega}_{T,i}(z); \quad z \in \mathcal{Z} \tag{25}$$

$$\Pi_{T,i}(x,z) = (1-\phi)y(x,z) - \omega_{T,i}(x,z); \quad x \in \mathcal{X},\ z \in \mathcal{Z}. \tag{26}$$

Finally, the hiring-stage profits satisfy:

$$\tilde{\Pi}_{T,ne,i}(z) = \tilde{\Pi}_{T,0}(z) - (\tilde{\omega}_{\tau,ne,i}(z) - \tilde{\omega}_{\tau,e,0}(z)) \tag{27}$$

$$\tilde{\Pi}_{T,ue,i}(z) = \tilde{\Pi}_{T,0}(z) - (\tilde{\omega}_{\tau,ue,i}(z) - \tilde{\omega}_{\tau,e,0}(z)) \tag{28}$$

for $\tau = 2, ..., T$, $i = 0, 1$, and $z \in \{z_0\}$. The next subsection analyzes wage equilibrium conditions.

3.3 Wages

In the following, we give conditions for wages as a solution to a Nash Bargaining problem faced by workers and employers. As discussed above, the agents' outside options depend on whether one considers a hiring stage or renegotiation stage and on the worker's UI and the job's EPL status. In the presentation that follows, we distinguish between the *hiring* and *renegotiation* stage.

(i) Hiring stage. For a new match, the wage satisfies:

$$\omega_{\tau,je,i}(z) = \arg\max \left(\tilde{V}_{\tau,je}(z) - \overline{V}_{\tau,j,i} \right)^{\gamma} \tilde{\Pi}_{\tau,je}(z)^{1-\gamma}; \tag{29}$$

$\tau = 2, ..., T; i = 0, 1; z \in \{z_0\}$, for all origin labor-force status $j \in \{n, u\}$. Observe that the worker's outside option is the nonemployment value satisfying (11) and (13), and that the employer's outside is simply zero due to free entry of vacancies and that fact that firing costs only apply to continuing matches.

We have the first-order condition

$$(1-\gamma)\left(\tilde{V}_{\tau,je}(z) - \overline{V}_{\tau,j,i} \right) = \gamma(1-\psi)\tilde{\Pi}_{\tau,je}(z), \tag{30}$$

for $\tau = 2, ..., T; i = 0, 1; z \in \{z_0\}$.

(ii) Renegotiation stage. Consider now a continuing match. The wage is the solution to

$$\begin{aligned} \tilde{\omega}_{\tau,i}(z) &= \arg\max \left(\tilde{V}_{\tau,e}(z) - \overline{V}_{\tau,e} \right)^{\gamma} \left(\tilde{\Pi}_{\tau,e}(z) - F_i \right)^{1-\gamma} \\ \omega_{\tau,i}(x,z) &= \arg\max \left(V_{\tau,e}(x,z) - \overline{V}_{\tau,e} \right)^{\gamma} \left(\Pi_{\tau,e}(x,z) - F_i \right)^{1-\gamma} \end{aligned} \tag{31}$$

with the FOC

$$\begin{aligned} (1-\gamma)\left(\tilde{V}_{\tau,je}(z) - \overline{V}_{\tau,j,i} \right) &= \gamma(1-\psi)\tilde{\Pi}_{\tau,je}(z); \quad z \in \mathcal{Z} \\ (1-\gamma)\left(V_{\tau,je}(x,z) - \overline{V}_{\tau,j,i} \right) &= \gamma(1-\psi)\Pi_{\tau,je}(x,z); \quad (x,z) \in \mathcal{X} \times \mathcal{Z}. \end{aligned} \tag{32}$$

for $\tau = 2, ..., T; i = 0, 1$.

Combining the FOC (30) and (32) with expressions for value functions (17) to (24) yields the following continuing (pre-tax) wage equations:

$$\tilde{\omega}_{\tau,i}(z) = \gamma(1-\phi)\int y(x',z)dG_x(x') + \frac{1-\gamma}{1-\psi}\,\underline{\omega}_\tau + \gamma\big(F_i - \mathcal{I}(\tau<T)\beta\sum_{i'}\mu_e(i'|i)F_{i'}\big); \quad (33)$$

$\tau = 2, ..., T,\ i = 0, 1,\ z \in \mathcal{Z}$ for an unrevealed-quality match and

$$\omega_{\tau,i}(x,z) = \gamma(1-\phi)y(x,z) + \frac{1-\gamma}{1-\psi}\,\underline{\omega}_\tau + \gamma\big(F_i - \mathcal{I}(\tau<T)\beta\sum_{i'}\mu_e(i'|i)F_{i'}\big). \quad (34)$$

$\tau = 2, ..., T,\ i = 0, 1,\ z \in \mathcal{X}\times\mathcal{Z}$ for a revealed-quality match. We define:

$$\frac{1}{1-\psi}\,\underline{\omega}_\tau \equiv \frac{1}{1-\psi}\Big[\overline{V}_{e,\tau} - \mathcal{I}(\tau<T)\,\beta\overline{V}_{e,\tau+1}\Big], \quad (35)$$

which can be interpreted as the pre-tax worker's reservation wage in a continuing match, determined by the current outside option net of the discounted expected unemployment option value for the next period.

Moreover, the same set of conditions implies that the hiring wage equations satisfy:

$$\tilde{\omega}_{\tau,ne,i}(z) = \tilde{\omega}_{\tau,0}(z) + \frac{1-\gamma}{1-\psi}\big(\underline{\omega}_{\tau,ne,i} - \underline{\omega}_{\tau,0}\big) - \gamma F_0 \quad (36)$$

$$\tilde{\omega}_{\tau,ue,i}(z) = \tilde{\omega}_{\tau,0}(z) + \frac{1-\gamma}{1-\psi}\big(\underline{\omega}_{\tau,ue,i} - \underline{\omega}_{\tau,0}\big) - \gamma F_0 \quad (37)$$

for $\tau = 2, ..., T,\ i = 0, 1,\ z \in \{z_0\}$, where

$$\frac{1}{1-\psi}\,\underline{\omega}_{\tau,je,i} \equiv \frac{1}{1-\psi}\Big[\overline{V}_{\tau,j,i} - \mathcal{I}(\tau<T)\,\beta\overline{V}_{\tau+1,e}\Big] \quad (38)$$

for $\tau = 2, ..., T; i = 0, 1; z \in \{z_0\}$, and $j \in \{n, u\}$, which is the pre-tax reservation wage of the worker, which explicitly depends on the UI and labor-force status (j, i) that determine the outside option in the negotiation (and negatively on the next-period expected nonemployment option value in the case of hiring).

3.4 Surplus functions

The first-order conditions of the Nash problems enable us to express the decision problem of workers and firms in terms of the gross surplus of a match. As per the above discussion, the surplus of a new match depends on the origin labor-force state of the worker and the UI status. As such, the surplus of a hiring-stage match satisfies the conditions:

$$\tilde{S}_{\tau,ne,i}(z) = \tilde{V}_{\tau,ne,i}(z) - \overline{V}_{\tau,n,i} + \tilde{\Pi}_{\tau,ne,i}(z) \quad (39)$$

$$\tilde{S}_{\tau,ue,i}(z) = \tilde{V}_{\tau,ue,i}(z) - \overline{V}_{\tau,u,i} + \tilde{\Pi}_{\tau,ue,i}(z); \quad (40)$$

$\tau = 2, ..., T,\ i = 0, 1,$ and $z \in \{z_0\}$. The surplus in a continuing job (with unrevealed and revealed match quality, respectively) is defined as

$$\tilde{S}_{\tau,i}(z) = \tilde{V}_{\tau,e,i}(z) - \overline{V}_{\tau,e} + \tilde{\Pi}_{\tau,i}(z) + F_i; \quad z \in \mathcal{Z} \tag{41}$$

$$S_{\tau,i}(x,z) = \tilde{V}_{\tau,e,i}(x,z) - \overline{V}_{\tau,e} + \Pi_{\tau,i}(x,z) + F_i; \quad (x,z) \in \mathcal{X} \times \mathcal{Z}, \tag{42}$$

for $\tau = 2, ..., T$ and $i = 0, 1$. Using the latter with expressions (16) to (28) we obtain the unrevealed-quality continuing surplus function

$$\tilde{S}_{\tau,i}(z) = (1-\phi)(1-\gamma\psi)\int y(x',z)dG_x(x') - \frac{1-\gamma\psi}{1-\psi}\underline{\omega}_\tau + (1-\gamma\psi)\big(F_i - \beta\sum_{i'}\mu_e(i'|i)F_{i'}\big)$$
$$+\beta\sum_{i'}\mu_e(i'|i)\int\left\{(1-\alpha)\max(\tilde{S}_{\tau+1,i'}(z'),0) + \alpha\int\max(S_{\tau+1,i'}(x',z'),0)dG_x(x')\right\}dG_z(z'|z), \tag{43}$$

for $\tau = 2, ..., T-1$, $i = 0, 1$, and $z \in \mathcal{Z}$, and the revealed-quality surplus

$$S_{\tau,i}(x,z) = (1-\phi)(1-\gamma\psi)y(x,z) - \frac{1-\gamma\psi}{1-\psi}\underline{\omega}_\tau + (1-\gamma\psi)\big(F_i - \beta\sum_{i'}\mu_e(i'|i)F_{i'}\big)$$
$$+\beta\sum_{i'}\mu_e(i'|i)\int\max(S_{\tau+1,i'}(x,z'),0)dG_z(z'|z), \tag{44}$$

for $\tau = 2, ..., T-1$, $i = 0, 1$, and $(x,z) \in \mathcal{X} \times \mathcal{Z}$. The terminal values satisfy

$$\tilde{S}_{T,i}(z) = (1-\phi)(1-\gamma\psi)\int y(x',z)dG_x(x') - \frac{1-\gamma\psi}{1-\psi}\overline{V}_{T,e}; \quad z \in \mathcal{Z} \tag{45}$$

$$S_{T,i}(x,z) = (1-\phi)(1-\gamma\psi)y(x,z) - \frac{1-\gamma\psi}{1-\psi}\overline{V}_{T,e}; \quad (x,z) \in \mathcal{X} \times \mathcal{Z}, \tag{46}$$

for $i = 0, 1$.

Finally, the surplus for a new, hiring-stage match solves

$$\tilde{S}_{\tau,ne,i}(z) = \tilde{S}_{\tau,0}(z) + \frac{1-\gamma\psi}{1-\psi}\big(\underline{\omega}_{\tau,ne,i} - \underline{\omega}_\tau\big) - (1-\gamma\psi)F_0$$
$$\tilde{S}_{\tau,ue,i}(z) = \tilde{S}_{\tau,0}(z) + \frac{1-\gamma\psi}{1-\psi}\big(\underline{\omega}_{\tau,ue,i} - \underline{\omega}_\tau\big) - (1-\gamma\psi)F_0; \tag{47}$$

$\tau = 2, ..., T$, $i = 0, 1$, and $z \in \mathcal{Z}$.

3.5 Policy functions

Optimal search effort. The optimal search effort, written in terms of the surplus function, is given by

$$s^*_{\tau,j,i} = \min\left\{(1/\chi_j)\left[\beta A\theta^{1-\eta}\frac{\gamma(1-\psi)}{1-\gamma\psi}\sum_{i'}\mu_o(i'|i)\max\big(\tilde{S}_{\tau+1,je,i'},0\big)\right]^{\frac{1}{\zeta}},\ 1\right\}, \tag{48}$$

for $\tau = 1, ..., T-1$, $i = 0, 1$, and $j \in \{n, u\}$. Moreover, $s^*_{\tau,j,i} = 0$ for $\tau = 0$ (by assumption) and $\tau = T$.

Labor-force participation. The probability of participating (i.e., of choosing unemployment) in $\tau + 1$ conditional on being in non-employment in period τ, and conditional on the origin state in $\{n, u, e\}$ and UI status i' is:

$$
\begin{aligned}
\mathcal{P}^{nu}_{\tau+1,i'} &= \frac{\exp\left(V_{\tau+1,u,i'} - \overline{c}_{nu}\right)}{\exp\left(V_{\tau+1,n,i'}\right) + \exp\left(V_{\tau+1,u,i'} - \overline{c}_{nu}\right)} \\
\mathcal{P}^{uu}_{\tau+1,i'} &= \frac{\exp\left(V_{\tau,u,i'}\right)}{\exp\left(V_{\tau+1,n,i'}\right) + \exp\left(V_{\tau+1,u,i'}\right)},
\end{aligned}
\tag{49}
$$

for all $\tau = 0, ..., T-1$, $i' = 0, 1$. Moreover, the probability of participating of an individual who is nonemployed at the end of period τ but coming from employment is:

$$
\mathcal{P}^{eu}_{\tau+1} = \frac{\exp\left(V_{\tau+1,u,1} - \overline{c}_{eu}\right)}{\exp\left(V_{\tau+1,n,1}\right) + \exp\left(V_{\tau+1,u,1} - \overline{c}_{eu}\right)},
\tag{50}
$$

for all $\tau = 0, ..., T-1$. Moreover, $\mathcal{P}^{un}_{\tau+1} = 1 - \mathcal{P}^{uu}_{\tau+1}$, $\mathcal{P}^{nn}_{\tau+1} = 1 - \mathcal{P}^{nu}_{\tau+1}$, and $\mathcal{P}^{en}_{\tau+1} = 1 - \mathcal{P}^{eu}_{\tau+1}$.

Matching and job separation.. Conditional on a contact between a worker and a firm, hiring takes place under the condition that

$$
\tilde{S}_{\tau,je,i} \geq 0,
\tag{51}
$$

for all $j \in \{U, N\}$ and all $i = 0, 1$. Denote by $\overline{\tau}_{je,i} \in \{0, ..., T\}$ the maximum age such that the above condition is satisfied.

There are joint worker-firm decisions on whether a job match is viable or not. These decisions can be expressed as reservation thresholds in terms of match productivity. A separation occurs in two cases: after the revelation of the match quality or after a productivity shock. Define $\tilde{z}_{\tau,i} \in Z$ and $z_{\tau,i} : \mathcal{X} \to \mathcal{Z}$ by

$$
\begin{aligned}
&\tilde{S}_{\tau,i}(\tilde{z}_{\tau,i}) = 0 \\
&S_{\tau,i}(x, z_{\tau,i}(x)) = 0.
\end{aligned}
\tag{52}
$$

In cases where $\tilde{z}_{\tau,i}$ and $z_{\tau,i}(x)$ are such that $\tilde{S}_{\tau,i}(\tilde{z}_{\tau,i}) > 0$ and $S_{\tau,i}(x, z_{\tau,i}(x)) > 0$, it is convenient for the following to let $\tilde{z}_{\tau,i} = \inf \mathcal{Z}$ and $z_{\tau,i}(x) = \inf \mathcal{Z}$.

State conditional transition probabilities. The UE and NE transition probabilities are given by:

$$\lambda_{\tau,ue,i} = A\theta^{1-\eta} s^*_{\tau,u,i} \sum_{i'} \mu_o(i'|i)\, \mathcal{I}\big(\tilde{S}_{\tau+1,ue,i'} \geq 0\big)$$
$$\lambda_{\tau,ne,i} = A\theta^{1-\eta} s^*_{\tau,n,i} \sum_{i'} \mu_o(i'|i)\, \mathcal{I}\big(\tilde{S}_{\tau+1,ne,i'} \geq 0\big), \tag{53}$$

for all $i = 0, 1$, and $\tau = 1, ..., T-1$. $\mathcal{I}(.)$ is the indicator function. These are defined as the probability of transiting from unemployment and non-participation to employment between age τ and $\tau + 1$ conditional on the UI status.

Moreover, the probability of transiting across U and N is:

$$\lambda_{\tau,nu,i} = \sum_{i'} \mu_o(i'|i) \Big[1 - A\theta^{1-\eta} s^*_{\tau,u,i} \mathcal{I}\big(\tilde{S}_{\tau+1,ne,i'} \geq 0\big)\Big] \mathcal{P}^{nu}_{\tau+1,i'}$$
$$\lambda_{\tau,un,i} = \sum_{i'} \mu_o(i'|i) \Big[1 - A\theta^{1-\eta} s^*_{\tau,n,i} \mathcal{I}\big(\tilde{S}_{\tau+1,ue,i'} \geq 0\big)\Big] \mathcal{P}^{un}_{\tau+1,i'}, \tag{54}$$

for all $\tau = 1, ..., T-1$, $i = 0, 1$. In an unrevealed-quality match, the probability of transiting to the out-of-work state $j \in \{n, u\}$ is

$$\tilde{\lambda}_{\tau,ej,i}(z) = \sum_{i'} \mu_e(i'|i) \Big[(1-\alpha) G_z(\tilde{z}_{\tau+1,i'}|z) + \alpha \int G_z(z_{\tau+1,i'}(x')|z) dG_x(x')\Big] \mathcal{P}^{ej}_{\tau+1}. \tag{55}$$

for all $\tau = 1, ..., T-1$, $i = 0, 1$, $z \in \mathcal{Z}$, and for all destination state $j \in \{u, n\}$.

Considering a revealed-quality match, we have

$$\lambda_{\tau,ej,i}(x, z) = \sum_{i'} \mu_e(i'|i) G_z(z_{\tau+1,i}(x)|z) \mathcal{P}^{ej}_{\tau+1}, \tag{56}$$

for all $\tau = 1, ..., T-1$, $i = 0, 1$, $(x, z) \in \mathcal{X} \times \mathcal{Z}$, and all $j \in \{u, n\}$.

Moreover, recall that all workers are born in nonparticipation and choose between nonparticipation and unemployment at the end of age $\tau = 0$. Hence, we have the age $\tau = 0$ transition probabilities:

$$\lambda_{0,nn,i} = \mathcal{P}^{nn}_{1,i}$$
$$\lambda_{0,nu,i} = \mathcal{P}^{nu}_{1,i}, \tag{57}$$

for $i = 0$, which, is, by assumptions, the value for the UI status at birth.

3.6 Labor-market flows and distributions

See appendix B.1.

3.7 Labor-market tightness

The free-entry condition implies, using the Cobb-Douglas functional form for the matching function:

$$\theta^{\eta} = \frac{\beta A}{c}\frac{1-\gamma}{1-\gamma\psi}\sum_{\tau=1}^{T-1}\sum_{i\in\{0,1\}}\mu_o(i'|i)\times\left\{\frac{s^*_{\tau,n,i}n_{\tau,i}}{\mathcal{L}^*_n+\mathcal{L}^*_u}\max\left(\tilde{S}_{\tau+1,ne,i'},0\right)+\frac{s^*_{\tau,u,i}u_{\tau,i}}{\mathcal{L}^*_n+\mathcal{L}^*_u}\max\left(\tilde{S}_{\tau+1,ue,i'},0\right)\right\}, \tag{58}$$

where

$$\mathcal{L}^*_n = \sum_{\tau=1}^{T-1}\sum_{i\in\{0,1\}} s^*_{\tau,n,i}n_{\tau,i} \tag{59}$$

$$\mathcal{L}^*_u = \sum_{\tau=1}^{T-1}\sum_{i\in\{0,1\}} u^*_{\tau,n,i}u_{\tau,i} \tag{60}$$

represent the effective measure of job seekers in nonparticipation and unemployment, respectively (total number of agents who are out of work in these two states multiplied by their optimal search intensity).

3.8 Equilibrium definition

Definition 1. *A steady-state equilibrium is a list of value functions* $\{V_{\tau,n,i}, V_{\tau,u,i} : \tau = 1, ..., T; i = 0, 1\}$*, surplus functions* $\{\tilde{S}_{\tau,ne,i}, \tilde{S}_{\tau,ue,i}, \tilde{S}_{\tau,i}, S_{\tau,i} : \tau = 2, ..., T; i = 0, 1\}$*, policy functions* $\{s^*_{\tau,n,i}, s^*_{\tau,u,i}, \mathcal{P}^{nu}_{\tau,i}, \mathcal{P}^{uu}_{\tau,i}, \mathcal{P}^{eu}_{\tau} : \tau = 0, ..., T; i = 0, 1\}$*,* $\{\tilde{z}_{\tau,i}, z_{\tau,i} : \tau = 2, ..., T; i = 0, 1\}$*, and* $\{\overline{\tau}_{ne,i}, \overline{\tau}_{ue,i}; i = 0, 1\}$*, wage functions* $\{\tilde{\omega}_{\tau,ne,i}, \tilde{\omega}_{\tau,ue,i}, \tilde{\omega}_{\tau,i}, \omega_{\tau,i} : \tau = 0, ..., T; i = 0, 1\}$*, labor market stocks* $\{n_{\tau,i}, u_{\tau,i} : \tau = 0, ..., T; i = 0, 1\}$*, and a labor-market tightness* θ *such that* (10)-(60) *are satisfied and such that labor-market stocks and distributions are time-invariant.*

4 Calibration

We calibrate the model and illustrate some of its key properties. We focus on the following five economies: France, Germany, Italy, Spain, and the U.K. We calibrate the model for men and women. We set a period to one quarter. In addition and for all economies, there are two sets of parameters: those that are uniform across economies vs. those specific to each economy. We describe these parameters below.

Functional forms, exogenous distributions, stochastic processes. We assume that the match quality x follows a log-normal distribution with parameters denoted μ_x and σ_x^2. We let $\mu_x = -\sigma_x^2/2$ so the match quality distribution has unconditional mean normalized to one, and we calibrate the variance of the log match quality σ_x^2 internally (see below). Moreover, we let the stochastic match-output component z, taken in log terms, follow a first-order autoregressive process with mean zero:

$$\ln z' = \rho_z \ln z + \varepsilon'.$$

with $\rho_z \in (0,1)$ the persistence parameter and $\varepsilon' \sim \mathcal{N}(0, \sigma_\varepsilon^2)$ is an i.i.d. innovation term.

Common technology parameters. For the following parameters, we use the same values for all countries and demographic groups. The discount factor β is 0.9902, consistent with an annual discount rate of 4 percent. As is standard in the literature, the vacancy-elasticity of the matching function η and the bargaining power of workers γ are both set to the same value of 0.5. Motivated by the observation that shocks in empirical wage-earnings equations are close to unit-root processes, we set $\rho_z = 0.975$ to make match productivity highly persistent.

Labor-market policies. The policy parameters are country specific. We use OECD data on retirement, UI benefits, EPL, and tax wedges to set the policy parameters.

The parameters $T, \overline{\mu}_o, \overline{\mu}_e, \psi, \phi$ are externally calibrated. We use estimates on the effective retirement age by country, for men and women, in OECD [2021] to set country-specific and gender-specific values for the retirement time horizon T. We set $\overline{\mu}_o = 0.2212$ in all countries to make eligibility for high UI benefits last one year on average. This choice is motivated by the observation that UI replacement ratios decline sharply after one year of unemployment in the countries under scrutiny but display, in comparison, low variation within the first year. Finally, we also set π_e to the same value so firing costs apply after one year on average. This choice captures the tenure-dependence schemes of EPL in European countries. Finally, we use OECD data from oec [2023] and set ϕ and ψ to equal the 2006-2016 average for VTA taxes and social security tax rates (employer and employee contributions).[15]

The parameters for firing costs F and UI benefits b_0 and b_1 are internally calibrated since these have calibration targets expressed in relation to the average equilibrium wage. We calibrate firing costs to equal the unweighted average mandated severance payments (in terms of the average equilibrium wage) obtained from the OECD EPL database (oec [2013]) for jobs with tenure from one to twelve years. This choice is motivated by evidence that mandated severance payments are lower bound for the value of nontransferable firing costs reflecting procedural, red-tape costs (Cahuc et al. [2019]), which correspond to the component that is relevant for match dissolution decisions. In addition, we calibrate unemployment benefits to match the (unweighted) average replacement ratios across unemployment duration levels from oec [2023].[16] More specifically, b_1 is set to target the average replacement ratio for individuals with unemployment duration from zero to 11 months and b_0 for 12 to 23 months (taking, here again, the average equilibrium wage as reference). The policy targets are shown in table 4.

Country-specific structural/policy-invariant parameters. The remaining parameters are: $A, c_v, \delta, \overline{c}_{eu}, \overline{c}_{nu}, \overline{c}_u, \chi_u, \chi_n, \overline{\pi}_e, \alpha, \sigma_x^2, \sigma_z^2, y_o$. These are policy-invariant parameters that describe technology, skills, and preferences. We treat these parameters as country-specific.

[15] We use social security tax rates for single individuals with average earnings.

[16] We take replacement ratios for single earners paid at the average wage.

Table 3: Common preset parameter values

β	discount factor	0.9902
γ	bargaining power	0.5
η	elasticity of matching	0.5
ρ_z	match output shocks: persistence	0.97
μ_u	UB, regime-change probability	0.22
μ_e	EPL, regime-change probability	0.22

We also allow a subset of these parameters to vary across genders. Specifically, the production and matching technology $A, c_v, \delta, \alpha, \sigma_x^2, \sigma_z^2$, are common to men and women; those related to non-work utility and workers' search activities $\chi_u, \chi_n, \zeta, y_o, \overline{c}_{eu}, \overline{c}_{nu}, \overline{c}_u$ are allowed to be different. We interpret these differences as reflecting heterogeneity in home production technologies due to factors such as childcare or family responsibility.

We first use aggregate (i.e., unconditional) transition rates between N, U, and E to discipline the search and home production parameters.[17] We normalize the unemployment-search marginal cost χ_u to one for men and let A be informed by the UE rate for men. We also use the UE rate for women to inform the same marginal cost χ_u for women, which determines the optimal equilibrium search intensity. Then, we use the five remaining unconditional transitions to identify the following five parameters: $y_0, \overline{c}_u, c_{eu}, c_{nu}, \chi_n$, for both men and women. Intuitively, y_0 (period home production) determines the value of being out of work and c_{eu} (unemployment search set-up costs from employment) determines the attractiveness of unemployment relative to nonparticipation after an employment separation. These two parameters are informed by EU and EN. In addition, c_{nu} (U set-up costs from N) is the direct costs of leaving nonparticipation for unemployment, whereas $\overline{c}_u$ (U search operating costs) governs the benefits of leaving unemployment for nonparticipation. These two parameters are identified by transitions between N and U. Finally, NE identifies the nonparticipation search cost parameter χ_n that determines the optimal search intensity of the nonparticipants.

Second, we use our data on employment separation rates (into U and N) to identify the production technology parameters. Indeed, as argued in the following, these parameters determine the distribution of separation rates for youths to prime-age workers. Within each country, we compute employment separation probabilities ($EN + EU$) for each gender/age cell for ages 20 to 55. We then compute the percentiles 10, 25, 75, and 90 across these cells and use these percentiles as targets for the parameters $\delta, \alpha, \sigma_x^2, \sigma_z^2$. The parameter δ and σ_x determine the lowest and highest separation rates across cells, and α shapes the thickness of the right distribution tails. These are informed by the percentiles 10, 75, and 90; we let σ_z^2 be determined by the percentile 25.

Lastly, we calibrate as follows the matching technology parameter A and c_v. We calibrate the model in partial equilibrium in the sense that we treat the probability of a contact $p(\theta)$ as an internal parameter. Second, we normalize the labor-market tightness in Germany to

[17]We compute age-adjusted averages for the transition rates by imposing the model age structure (uniform population across age groups). Further, we compute these averages for individuals with age 20-59.

one and deduce value of the vacancy posting cost c_v in this country that is consistent with this normalization (given the calibrated values for A and $p(\theta)$) using the free-entry condition (58). Then, we solve for the value for the vacancy posting costs across the four other countries such that the model matches the empirical vacancy rates in France, Italy, Spain, and the U.K., expressed in relative terms with that in Germany. We obtain data for vacancy rates from the ECB Statistical Data Warehouse (ECB [2023]). The resulting parameters are shown in tables 3 and 4.

Table 4: Country-specific parameters

		France	**Germany**	**Italy**	**Spain**	**U.K.**
Institutions						
T	retirement age	168	176	172	180	180
b_0	UB, low level	0.19	0.16	0.02	0.25	0.13
b_1	UB, high level	0.19	0.29	0.15	0.25	0.13
F	firing costs	0.37	0.59	0.94	0.96	0.10
ψ	wage tax rate	0.56	0.41	0.42	0.36	0.20
ϕ	output tax rate	0.11	0.11	0.11	0.09	0.10
Technology/skills						
A	matching efficiency	0.40	0.28	0.26	0.42	0.19
$c_v/E(y)$	vacancy posting cost / mean output	2.73	1.01	1.42	2.33	0.92
δ	exog. separation	0.008	0.009	0.011	0.021	0.007
σ_x^2	log match quality, variance	0.87	0.88	0.91	0.90	0.96
α	match quality, revelation prob.	0.39	0.39	0.39	0.39	0.39
σ_ε^2	match output shocks: innovation variance	0.003	0.003	0.003	0.003	0.003

		France		**Germany**		**Italy**		**Spain**		**U.K.**	
Search/leisure		*Men*	*Wom.*	*Men*	*Wom.*	*Men*	*Wom.*	*Men*	*Wom.*	*Men*	*Wom.*
y_o	non-work utility	0.01	0.09	0.07	0.25	0.03	0.19	0.02	0.19	0.03	0.19
$\bar{c}_u$	period unemp. cost	0.19	0.23	0.17	0.21	0.08	0.12	0.31	0.31	0.57	0.39
c_{eu}	unemp. entry cost, from emp.	2.47	2.46	3.40	3.62	2.80	2.70	2.23	1.66	2.38	3.27
c_{nu}	unemp. entry cost, from nonpart.	8.15	7.83	7.59	7.05	6.86	6.33	7.39	6.12	6.43	6.72
χ_u	search cost, slope, in unemp.	1.00	0.88	1.00	0.63	1.00	0.82	1.00	0.74	1.00	0.91
χ_n	search cost, slope, in nonpart.	7.70	7.74	3.70	2.84	4.85	5.80	6.67	5.56	5.31	3.61

5 Model fit

The model fit to targeted institutions and transition rates is shown in table 5. The calibrated model fits almost exactly the policy targets. It fits closely the unconditional transition probabilities, except for the UN rates that the model systematically overshoots. Finally, the model fits very closely the distribution of the employment separation rates.

In addition, we show the model fit to nontargeted moments. First, we show in figure 4 that the calibrated model matches the untargeted employment age profiles for all countries. In 5, we represent scatter plots of transition probabilities by country, gender, and age in the data and as generated by the calibrated model to gauge the fit to the untargeted transition (gender and age) distributions within countries. The model captures the large variation in transition rates well, as shown by the panels where a substantial mass of points is located along the 45-degree line. A notable exception is the UN rate, for which the model overshoots a substantial mass of points. That being said, the majority of the points are still around the 45-degree line, even for the UN rate. We complement this scatter plot with figures displaying the fit to the entire age profiles of transition probabilities by country and gender (in subsection C.1 of the Appendix). Consistent with the scatter plot, the model captures a significant fraction of the age variation in the data for all transitions (except for UN rates). Lastly, in subsection C.2 of the Appendix, we demonstrate that the model is qualitatively consistent with the employment cross-country variance age profile (figure C11) and that it fits very well the unemployment variance profile (figure C12).

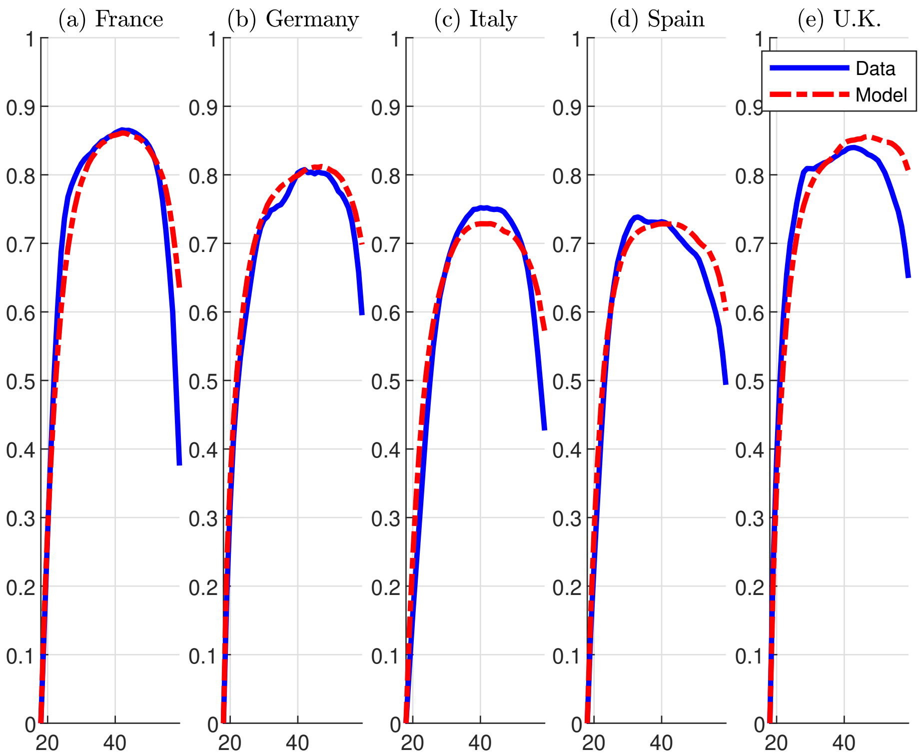


Figure 4: Calibrated model fit to untargeted employment rates

Table 5: Model fit to targeted moments

	France		**Germany**		**Italy**		**Spain**		**U.K.**	
	Target	*Model*	*Target*	*Model*	*Target*	*Model*	*Target*	*Model*	*Target*	*Model*
Institutions										
$b_0/\overline{w}$	0.65	0.65	0.33	0.33	0.06	0.06	0.59	0.59	0.26	0.26
$b_1/\overline{w}$	0.67	0.67	0.60	0.60	0.41	0.41	0.59	0.59	0.26	0.26
$F/\overline{w}$	1.67	1.67	2.17	2.17	4.33	4.33	4.33	4.33	0.48	0.48
Labor-market transitions, men										
NU	2.38	2.38	1.63	1.63	3.13	3.13	2.89	2.89	2.21	2.21
NE	4.76	4.75	8.05	8.65	4.82	4.61	4.70	4.72	6.67	6.36
UN	1.18	1.21	2.20	2.19	2.52	2.58	1.71	1.70	4.94	4.76
UE	16.72	16.99	17.86	17.82	12.95	13.89	18.21	17.74	20.25	23.55
EN	0.28	0.28	1.06	1.06	0.68	0.62	0.59	0.59	0.75	0.75
EU	1.71	1.70	1.79	1.72	1.64	1.64	3.66	3.01	1.00	1.00
Labor-market transitions, women										
NU	1.28	1.28	1.16	1.16	2.18	2.18	3.50	3.50	1.02	1.02
NE	4.59	3.82	7.61	7.60	2.72	2.72	3.94	3.94	6.92	6.92
UN	2.47	2.74	4.98	5.14	6.15	6.16	4.42	4.65	7.65	7.70
UE	15.90	16.25	16.94	16.94	11.57	11.57	15.75	16.06	21.34	20.94
EN	0.69	0.69	3.06	2.68	1.65	1.65	1.32	1.32	2.16	2.08
EU	1.85	1.85	1.44	1.44	2.01	2.03	4.46	4.34	0.73	0.73
Employment separation rate: percentile (gender/age cells)										
10	1.19	1.21	1.60	1.65	1.78	1.74	3.15	3.21	1.14	1.14
25	1.41	1.44	1.91	2.23	1.96	1.99	3.56	3.44	1.29	1.33
75	2.91	2.86	5.96	4.16	4.23	3.60	5.83	5.28	3.54	2.86
90	5.35	5.33	7.85	7.43	6.06	6.09	9.03	7.17	4.87	5.14

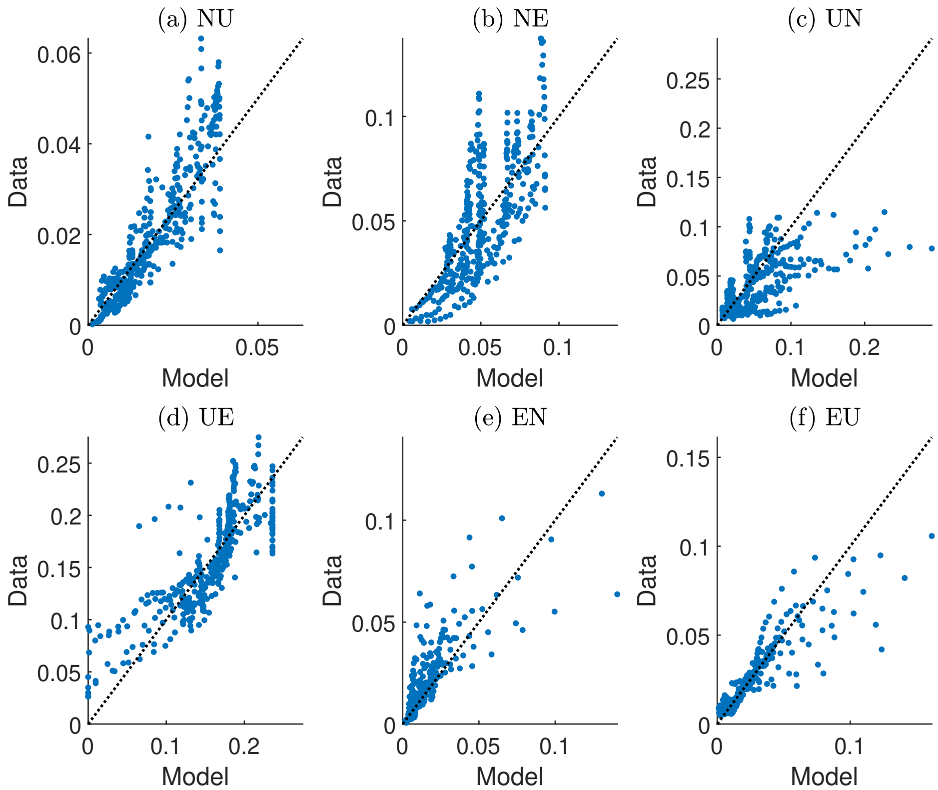


Figure 5: Transition probabilities across country/gender/age cells: data vs. calibrated model

6 Quantitative results

6.1 Cross-country employment decomposition

We use the calibrated model to decompose the differences in the aggregate employment rates into three components reflecting differences originating in (i) the technology of production (ii) the technology of matching, search and home production, and (iii) policies. We focus on the following five calibrated economies: France, Germany, Italy, Spain, and the U.K. Define the following vector of country-specific parameters:

$$\vartheta = (\sigma_x^2, \sigma_z^2, \alpha, \delta) \tag{61}$$

$$\varphi = (A, c_v, \chi_u, \chi_n, c_{eu}, c_{nu}, \bar{c}_u, y_0) \tag{62}$$

$$\lambda = (T, b_0, b_1, F, \psi, \phi); \tag{63}$$

the vector $\vartheta \in \Theta \subset \mathbb{R}^{L_\vartheta}$ of size L_ϑ has parameters describing technology, $\varphi \in \Phi$ captures search, and $\lambda \in \Lambda$ captures policies. Consider $E : \Theta \times \Phi \times \Lambda \to [0, 1]$, the employment rate generated by the model as a function of the vector of parameters $(\vartheta, \varphi, \lambda)$. We consider the following additive decomposition for the aggregate model employment difference between country c and a reference country r:

$$\begin{aligned} E(\vartheta^c, \varphi^c, \lambda^c) - E(\vartheta^r, \varphi^r, \lambda^r) = & \underbrace{E(\vartheta^c, \varphi^c, \lambda^c) - E(\vartheta^r, \varphi^c, \lambda^c)}_{\text{technology}} \\ & + \underbrace{E(\vartheta^r, \varphi^c, \lambda^c) - E(\vartheta^r, \varphi^r, \lambda^c)}_{\text{search}} \\ & + \underbrace{E(\vartheta^r, \varphi^r, \lambda^c) - E(\vartheta^r, \varphi^r, \lambda^r)}_{\text{policy}} . \end{aligned} \tag{64}$$

Since this decomposition is path-dependent, we compute Shapley values associated with the six possible decomposition sequences. We apply this decomposition to each country, age, and gender and compute the variance contribution of each component (technology, search, and policies) to the total employment cross-country variance (by age and gender), taking as reference a hypothetical country with the cross-country average parameter values. Figure 6 shows the results. We find the following. The sources of the cross-country employment differences

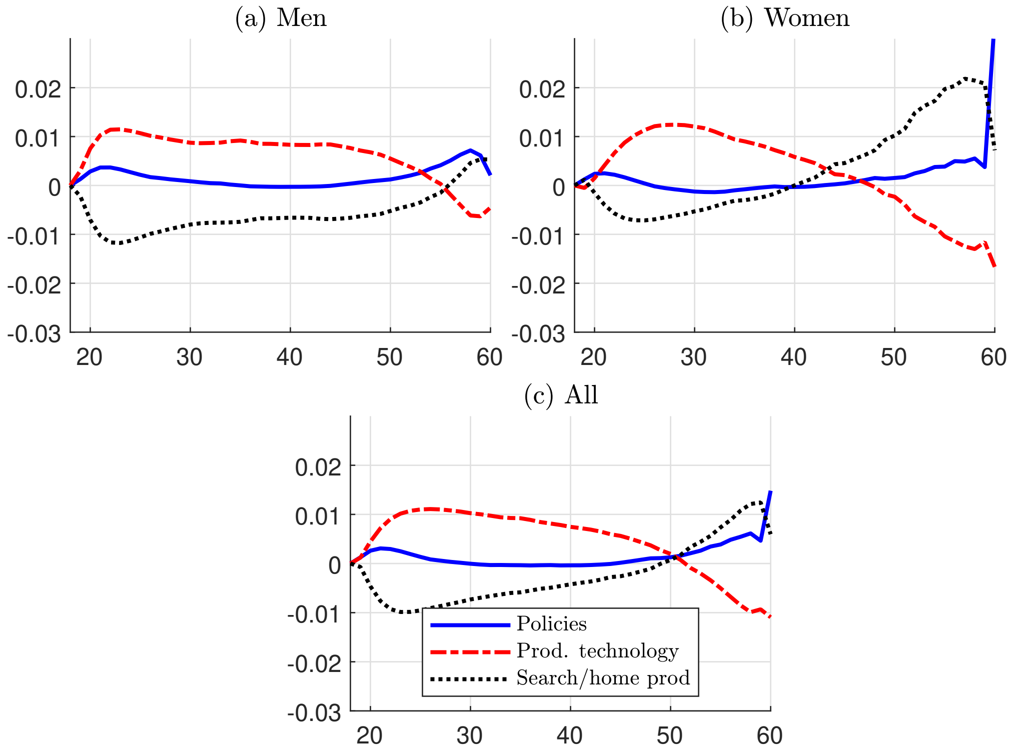


Figure 6: Model-based life-cycle employment variance decomposition

vary substantially with age. Panel (c), for both men and women, shows that the technology contribution decreases monotonically with age, whereas the contribution of policies and search increases monotonically (between ages 25 and 59). The contribution of technology-related factors is positive for youths and prime-age workers and negative for those with more than 50. The search-related factors tend to decrease the cross-country variance, except for the older workers, where these have a positive contribution. The contribution of policies is negligible, except for the employment rate of older individuals. Panels (a) and (b) show the results for men and women. The patterns are similar, except after age 40, where search and technology become (positive and negative) high contributors to the employment variance for women.

7 Conclusion

In this paper, we provide a comprehensive account of the relationship between cross-country differences in aggregate employment and disaggregated differences in worker flows along the life cycle. Overall, our results shed light on the importance of separations when accounting for differences in employment outcomes both aggregate and over the life cycle across Europe. Our result complements the empirical literature on the importance of the worker flows in explaining the dynamics of unemployment. We also go beyond description by developing a model that speaks to the facts we document. Our model features worker flows across employment, unemployment and nonparticipation, that move over the life cycle in ways that are qualitatively and quantitatively in line with the data. We use the model to draw inferences about the role of technology, preferences for work, and labor market institutions in explaining the life-cycle profiles of worker flows.

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Appendix: For Online Publication

A Additional Data Information

Table A1 describe the data sources, including the sample period and number of individual observations for each country, of our empirical analysis. For most countries, data come from the EU-SILC. For Germany, we use data from GSOEP. For France, Switzerland and the U.K., we have data from EU-SILC as well as from the labor force surveys of each country, which we use to cross-validate our results from the EU-SILC data.

Table A2a and A2b report the average of transition probabilities for each country analyzed. These data moments are interesting in their own rights, and in order to facilitate interpretations, we organize countries into five main groups: Nordic, Western, Southern, Baltic, and Eastern countries. Since much of our analysis in the main text focuses on the largest European economies, it concerns countries that belong to the Western (Germany, France and the U.K.) and Southern (Italy and Spain) parts of Europe.

Tables A3a and A3b are the counterparts to Table 1 and 2 in the main text. The Tables show how the gap between employment in each country and average employment is accounted for by demographics, initial conditions, and transition probabilities. For transition probabilities, the results are further broken down into the contribution of each transition rate. Recall that the latter decomposition is not unique. To obtain the contribution of each transition rate to the employment gap (residual, that is to say after netting out the effects of demographics and initial conditions), we apply the Shapley value.

Table A1: Description of data sources

Country	Source	Year Min	Year Max	Age	Female	Individuals	Observations
Austria	EU-SILC	2004	2019	48.2	0.53	63479	172595
Belgium	EU-SILC	2004	2019	47.3	0.52	63122	173156
Bulgaria	EU-SILC	2006	2019	51.5	0.53	51013	172851
Switzerland	EU-SILC	2011	2019	49.7	0.53	36681	93712
Cyprus	EU-SILC	2005	2019	46.6	0.53	44544	135410
Czech republic	EU-SILC	2005	2019	49.5	0.53	71131	228953
Germany	GSOEP	2003	2015	47.5	0.53	60828	322811
Denmark	EU-SILC	2003	2019	51.3	0.52	39808	106829
Estonia	EU-SILC	2004	2019	47.0	0.54	51368	179454
Spain	EU-SILC	2004	2019	48.7	0.52	161371	502663
Finland	EU-SILC	2004	2019	48.9	0.50	40409	150386
France	EU-SILC	2004	2019	48.8	0.53	62525	256040
Greece	EU-SILC	2003	2019	51.6	0.52	121442	348734
Croatia	EU-SILC	2010	2019	51.1	0.53	57544	142846
Hungary	EU-SILC	2005	2019	48.4	0.55	92387	263799
Ireland	EU-SILC	2004	2019	49.0	0.52	47124	109214
Iceland	EU-SILC	2007	2018	45.0	0.50	19829	43032
Italy	EU-SILC	2004	2019	50.0	0.52	234286	653550
Lithuania	EU-SILC	2005	2019	50.8	0.55	36716	152161
Luxembourg	EU-SILC	2003	2019	44.7	0.51	42422	140915
Latvia	EU-SILC	2005	2019	50.4	0.58	56172	161915
Malta	EU-SILC	2006	2019	46.0	0.51	30964	113585
Netherlands	EU-SILC	2005	2019	50.3	0.54	46373	133104
Norway	EU-SILC	2003	2019	45.8	0.50	47492	119376
Poland	EU-SILC	2005	2019	48.1	0.54	168513	495278
Portugal	EU-SILC	2004	2019	48.4	0.54	49648	317472
Romania	EU-SILC	2007	2019	50.6	0.52	58012	201097
Serbia	EU-SILC	2013	2019	48.9	0.52	37991	100007
Sweden	EU-SILC	2004	2019	49.8	0.51	26749	81740
Slovenia	EU-SILC	2005	2019	45.8	0.51	138137	352995
Slovakia	EU-SILC	2005	2019	45.3	0.54	32346	191934
United Kingdom	EU-SILC	2005	2018	51.2	0.53	117295	252896
Total						**2207721**	**6870510**

NOTE: All data (except for Germany) comes from the the Statistics on Income and Living Conditions (EU-SILC) survey collected by Eurostat. Data for Germany comes from the German Socio-Economic Panel (GSOEP).

Table A2a: Average transition probabilities: Men

	Aged 16 to 65						Aged 25 to 54					
	EU	*EN*	*UE*	*UN*	*NE*	*NU*	*EU*	*EN*	*UE*	*UN*	*NE*	*NU*
Nordic countries:												
Denmark	1.27	1.58	17.89	8.85	6.20	2.28	1.17	0.80	18.71	5.84	7.62	3.03
Finland	2.57	3.29	16.75	6.39	10.49	2.75	2.34	1.72	18.67	5.11	14.12	4.81
Iceland	1.60	3.78	30.44	7.58	34.20	5.18	1.48	1.98	30.98	6.71	27.49	6.77
Norway	0.51	1.37	17.32	5.94	5.71	1.21	0.51	0.77	15.77	5.68	7.81	1.81
Sweden	1.46	2.62	27.66	13.68	13.96	4.33	1.14	1.16	30.81	8.51	17.07	4.96
Average	**1.48**	**2.53**	**22.01**	**8.49**	**14.11**	**3.15**	**1.33**	**1.29**	**22.99**	**6.37**	**14.82**	**4.28**
Western Europe:												
Austria	2.12	1.34	26.08	4.68	4.46	1.26	1.97	0.57	28.22	3.02	7.70	2.31
Belgium	1.03	1.10	7.61	4.37	3.05	2.05	0.93	0.74	10.82	2.54	5.60	2.61
Switzerland	0.61	1.11	25.49	6.83	7.80	1.24	0.52	0.43	27.51	5.61	11.46	2.58
Germany	0.93	0.82	9.64	4.06	4.65	1.25	0.77	0.29	10.48	2.46	7.04	3.01
France	1.57	0.71	13.82	2.11	1.82	0.90	1.39	0.18	15.55	1.21	3.78	2.02
Ireland	1.77	1.20	9.22	2.71	4.54	1.92	1.68	0.49	10.01	2.13	5.46	2.72
Luxembourg	0.94	0.50	16.35	3.12	1.47	0.63	0.86	0.23	17.62	1.99	4.23	1.57
Netherlands	0.89	1.45	11.56	3.74	6.15	0.79	0.84	0.75	14.20	2.69	11.57	2.27
United Kingdom	1.05	1.10	19.87	5.92	5.02	1.56	0.91	0.54	20.04	4.70	5.39	2.09
Average	**1.21**	**1.04**	**15.52**	**4.17**	**4.33**	**1.29**	**1.10**	**0.47**	**17.16**	**2.93**	**6.91**	**2.35**
Southern Europe:												
Cyprus	3.03	0.66	27.26	3.03	2.57	1.94	2.86	0.23	29.24	2.06	4.88	3.46
Spain	3.60	0.78	16.96	2.12	3.27	1.92	3.49	0.36	18.48	1.43	4.37	3.43
Greece	2.80	0.66	17.49	1.88	1.85	1.80	2.83	0.26	18.64	1.15	2.97	2.86
Italy	1.62	1.00	12.33	3.02	2.83	1.87	1.55	0.60	13.57	2.45	6.97	3.60
Malta	0.70	0.97	11.60	3.12	3.16	0.81	0.64	0.41	11.02	2.06	4.77	1.73
Portugal	2.64	2.21	14.83	3.66	6.73	2.25	2.55	1.97	15.45	3.00	6.91	2.96
Average	**2.40**	**1.05**	**16.75**	**2.81**	**3.40**	**1.76**	**2.32**	**0.64**	**17.73**	**2.03**	**5.14**	**3.01**
Baltic States:												
Estonia	2.06	1.16	16.81	3.81	4.98	1.56	1.95	0.65	17.06	2.46	5.50	1.61
Lithuania	2.30	1.07	14.77	2.57	4.01	1.55	2.22	0.64	15.08	1.75	3.82	2.25
Latvia	3.06	0.98	16.13	2.56	4.07	1.98	2.99	0.52	16.57	1.75	4.93	3.09
Average	**2.47**	**1.07**	**15.90**	**2.98**	**4.35**	**1.69**	**2.39**	**0.60**	**16.24**	**1.98**	**4.75**	**2.32**
Eastern Europe:												
Bulgaria	2.82	0.89	13.18	1.30	3.06	1.44	2.67	0.42	14.05	0.79	4.78	1.52
Czech Republic	1.10	0.47	16.04	2.62	1.91	1.17	0.94	0.12	16.64	1.22	3.25	1.73
Croatia	3.40	1.69	10.36	1.32	5.50	1.72	3.13	0.71	10.73	0.84	5.33	1.51
Hungary	2.63	1.01	23.23	3.45	2.67	1.19	2.51	0.55	25.27	2.61	4.79	1.73
Poland	1.93	1.08	17.89	2.49	3.54	1.49	1.77	0.67	19.27	1.86	4.88	1.58
Romania	0.42	0.51	10.83	2.90	1.65	0.57	0.42	0.34	12.03	2.59	3.29	1.12
Slovenia	1.46	0.50	13.55	8.23	1.82	2.19	1.28	0.18	15.53	6.38	3.75	5.53
Slovakia	1.38	0.93	13.32	2.36	2.98	1.81	1.21	0.62	13.31	1.38	4.72	2.31
Average	**1.89**	**0.89**	**14.80**	**3.08**	**2.89**	**1.45**	**1.74**	**0.45**	**15.85**	**2.21**	**4.35**	**2.13**
European Average	**1.78**	**1.24**	**16.66**	**4.21**	**5.36**	**1.76**	**1.66**	**0.64**	**17.78**	**3.03**	**6.98**	**2.73**

NOTE: The entries in the table are averages of quarterly transition probabilities expressed in percentage point. The last row of each country group reports the (unweighted) average of the numbers in each column.

Table A2b: Average transition probabilities: Women

	Aged 16 to 65						Aged 25 to 54					
	EU	*EN*	*UE*	*UN*	*NE*	*NU*	*EU*	*EN*	*UE*	*UN*	*NE*	*NU*
Nordic countries:												
Denmark	1.17	2.36	17.22	10.04	5.80	2.27	1.18	1.37	18.74	8.37	6.97	4.15
Finland	2.13	4.69	18.32	8.61	11.64	2.15	1.89	3.24	20.74	7.53	14.11	3.03
Iceland	1.28	4.32	28.13	13.84	20.47	3.91	1.32	2.87	30.13	12.35	17.92	4.95
Norway	0.57	2.22	16.92	5.71	5.39	0.69	0.56	1.61	16.90	5.08	7.70	1.20
Sweden	1.21	3.98	25.92	16.49	15.19	3.52	1.04	2.26	26.34	12.63	16.76	4.09
Average	**1.27**	**3.52**	**21.30**	**10.94**	**11.70**	**2.51**	**1.20**	**2.27**	**22.57**	**9.19**	**12.69**	**3.49**
Western Europe:												
Austria	2.00	2.55	21.42	7.11	4.09	0.96	1.93	1.88	22.68	6.16	6.21	1.51
Belgium	1.26	1.67	8.52	4.36	2.95	1.26	1.16	1.40	10.77	3.64	4.89	1.44
Switzerland	0.70	2.19	19.44	7.95	6.51	0.90	0.67	1.54	20.00	7.42	8.31	1.33
Germany	0.89	1.71	8.15	5.31	4.98	1.33	0.79	1.36	8.88	4.54	6.54	1.98
France	1.67	1.04	13.38	3.14	2.17	0.69	1.56	0.57	15.25	2.44	3.81	0.98
Ireland	1.69	2.80	19.44	6.90	3.96	0.84	1.56	2.25	20.57	6.46	4.29	0.98
Luxembourg	1.08	1.32	16.74	6.09	2.02	0.57	1.07	1.18	16.36	5.86	3.75	0.76
Netherlands	0.87	1.79	8.80	3.60	4.66	0.61	0.88	1.19	11.03	3.02	6.50	1.16
United Kingdom	0.75	2.46	21.53	7.88	5.48	0.83	0.67	2.00	21.34	7.32	6.80	0.94
Average	**1.21**	**1.95**	**15.27**	**5.82**	**4.09**	**0.89**	**1.14**	**1.49**	**16.32**	**5.21**	**5.68**	**1.23**
Southern Europe:												
Cyprus	3.67	0.94	28.24	3.49	2.11	1.40	3.45	0.61	29.27	3.03	3.13	1.33
Spain	4.39	1.41	14.88	4.59	2.68	2.52	4.38	1.02	15.68	4.27	3.28	3.85
Greece	3.23	1.63	12.87	2.80	1.73	1.21	3.31	1.28	13.63	2.67	2.40	1.52
Italy	1.88	1.98	10.80	6.62	1.93	1.53	1.90	1.63	11.54	6.60	2.86	2.11
Malta	0.50	2.15	14.47	8.74	2.19	0.28	0.37	1.77	14.34	8.85	2.45	0.24
Portugal	2.89	3.23	14.56	5.35	6.13	2.31	2.86	2.96	14.80	4.93	7.42	2.77
Average	**2.76**	**1.89**	**15.97**	**5.26**	**2.79**	**1.54**	**2.71**	**1.55**	**16.54**	**5.06**	**3.59**	**1.97**
Baltic States:												
Estonia	1.36	2.04	18.52	6.86	5.51	1.11	1.42	1.58	18.55	5.64	8.08	1.55
Lithuania	1.52	1.52	13.38	4.19	3.80	1.11	1.51	1.13	14.24	3.36	5.98	1.92
Latvia	2.11	1.84	16.29	5.19	4.14	2.08	2.11	1.43	16.36	4.38	6.22	3.38
Average	**1.67**	**1.80**	**16.06**	**5.41**	**4.48**	**1.43**	**1.68**	**1.38**	**16.39**	**4.46**	**6.76**	**2.29**
Eastern Europe:												
Bulgaria	2.41	1.44	11.13	2.66	2.51	1.18	2.43	0.90	12.36	1.89	4.80	1.86
Czech Republic	1.26	1.51	13.64	3.78	2.26	1.02	1.21	1.18	14.02	2.66	5.09	1.88
Croatia	3.40	2.04	9.56	2.73	4.02	2.14	3.17	0.74	9.52	2.49	3.25	4.11
Hungary	2.03	1.92	19.79	5.74	2.66	1.04	2.00	1.33	20.97	5.09	4.88	1.62
Poland	1.78	1.83	12.63	4.43	2.77	1.20	1.69	1.29	12.89	4.10	3.91	1.86
Romania	0.22	1.36	7.93	4.32	1.83	0.19	0.22	1.13	8.35	4.28	3.05	0.16
Slovenia	1.65	0.58	12.03	8.38	1.27	1.92	1.55	0.29	13.02	7.01	3.43	6.09
Slovakia	1.29	1.78	11.69	3.70	2.88	1.47	1.25	1.45	11.51	3.09	5.71	2.58
Average	**1.75**	**1.56**	**12.30**	**4.47**	**2.52**	**1.27**	**1.69**	**1.04**	**12.83**	**3.83**	**4.27**	**2.52**
European Average	**1.71**	**2.08**	**15.69**	**6.15**	**4.70**	**1.43**	**1.65**	**1.50**	**16.48**	**5.39**	**6.14**	**2.17**

NOTE: The entries in the table are averages of quarterly transition probabilities expressed in percentage point. The last row of each country group reports the (unweighted) average of the numbers in each column.

Table A3a: Decomposing the employment gap: Men

	Total gap	Demog-raphics	Initial cond.	Transition probab.	Transition probablities					
					EU	*EN*	*UE*	*UN*	*NE*	*NU*
Nordic countries:										
Denmark	1.32	0.27	-0.52	1.57	1.54	-1.86	0.93	-1.32	2.02	0.26
Finland	-5.42	-0.18	-0.14	-5.10	-3.69	-8.36	1.08	-0.66	5.85	0.68
Iceland	9.61	-1.00	0.32	10.30	0.51	-7.11	3.98	-0.52	12.51	0.93
Norway	1.21	-1.60	-1.08	3.89	5.71	-1.54	0.55	-0.93	0.63	-0.53
Sweden	7.04	-0.56	-0.04	7.63	0.92	-3.71	3.49	-0.98	7.08	0.84
Average	**2.75**	**-0.61**	**-0.29**	**3.66**	**1.00**	**-4.52**	**2.00**	**-0.88**	**5.62**	**0.43**
Western Europe:										
Austria	3.10	0.10	0.07	2.93	-1.27	-0.93	3.97	-0.34	1.55	-0.06
Belgium	-5.51	-0.22	0.05	-5.34	3.09	-2.78	-3.86	-0.10	-1.74	0.05
Switzerland	14.73	0.72	1.07	12.93	4.65	2.82	2.47	-0.29	3.52	-0.24
Germany	6.15	-0.03	0.49	5.69	4.10	3.25	-2.75	-0.05	1.06	0.08
France	-2.44	-1.43	-1.21	0.20	0.43	3.35	-1.35	1.29	-3.08	-0.45
Ireland	-7.40	-3.06	-0.39	-3.95	-0.81	0.15	-4.30	0.16	0.72	0.13
Luxembourg	1.13	1.15	-1.20	1.18	3.05	2.03	-0.25	0.31	-3.17	-0.80
Netherlands	4.09	1.28	-0.31	3.12	3.23	-2.92	-0.62	0.45	3.36	-0.39
United Kingdom	5.29	0.35	-0.14	5.08	2.69	0.49	1.58	-0.89	1.31	-0.11
Average	**2.13**	**-0.12**	**-0.17**	**2.43**	**2.13**	**0.61**	**-0.57**	**0.06**	**0.39**	**-0.20**
Southern Europe:										
Cyprus	-3.22	-3.32	-0.19	0.30	-4.87	3.53	4.57	0.63	-3.12	-0.44
Spain	-4.77	1.24	-0.15	-5.87	-7.42	1.88	0.70	1.25	-2.47	0.20
Greece	-5.10	1.12	-0.65	-5.58	-4.64	1.92	1.00	1.20	-4.85	-0.21
Italy	-3.27	1.06	0.08	-4.41	-0.28	-1.08	-2.02	0.25	-1.62	0.33
Malta	3.22	-0.83	0.42	3.63	5.38	1.15	-1.91	0.32	-0.95	-0.38
Portugal	-8.25	-0.79	0.78	-8.24	-3.83	-7.60	0.07	0.14	2.80	0.17
Average	**-3.57**	**-0.25**	**0.05**	**-3.36**	**-2.61**	**-0.03**	**0.40**	**0.63**	**-1.70**	**-0.05**
Baltic States:										
Estonia	-4.77	-1.52	-0.50	-2.75	-1.96	-1.01	0.75	-0.28	0.19	-0.44
Lithuania	-6.85	-1.30	0.15	-5.70	-2.95	-1.23	-0.35	0.60	-1.50	-0.27
Latvia	-5.76	-0.90	0.20	-5.06	-5.84	-0.91	0.51	0.87	0.04	0.28
Average	**-5.79**	**-1.24**	**-0.05**	**-4.50**	**-3.58**	**-1.05**	**0.30**	**0.40**	**-0.42**	**-0.14**
Eastern Europe:										
Bulgaria	-5.74	-0.23	0.13	-5.64	-5.16	1.10	-1.64	1.90	-1.43	-0.42
Czech Republic	3.01	-0.41	-1.18	4.60	2.33	6.30	0.16	1.73	-5.00	-0.91
Croatia	-13.63	-0.44	-0.04	-13.15	-6.81	-4.77	-4.67	1.31	1.79	-0.01
Hungary	-4.86	-0.88	0.09	-4.06	-3.67	-1.15	3.09	0.21	-2.06	-0.48
Poland	-2.62	-0.13	0.26	-2.75	-1.01	-2.06	0.94	0.51	-0.75	-0.38
Romania	7.44	0.21	2.62	4.61	7.23	5.55	-2.80	0.86	-5.03	-1.20
Slovenia	-3.17	0.65	-0.02	-3.80	0.44	2.91	-0.91	-2.07	-5.17	1.00
Slovakia	-3.53	-1.45	0.41	-2.49	1.31	-0.27	-1.79	1.23	-2.46	-0.51
Average	**-2.89**	**-0.34**	**0.28**	**-2.84**	**-0.67**	**0.95**	**-0.95**	**0.71**	**-2.51**	**-0.36**

NOTE: The entries in the table are employment gaps (relative to the population-weighted average of employment across countries) expressed in percentage point. The first column shows the raw employment gap; the second and third columns show the gap explained by differences in demographics and initial conditions, respectively; the fourth column shows the gap explained by differences in transition probabilities. The latter is decomposed into the gap explained by each transition probability in the remaining columns of the table. The last row of each country group reports the (unweighted) average of the numbers in each column.

Table A3b: Decomposing the employment gap: Women

	Total gap	Demog-raphics	Initial cond.	Transition probab.	Transition probablities *EU*	*EN*	*UE*	*UN*	*NE*	*NU*
Nordic countries:										
Denmark	4.81	-0.36	-0.53	5.70	1.72	-0.45	1.46	-1.02	2.86	1.12
Finland	3.41	-0.55	-0.14	4.10	-1.75	-8.89	2.45	-0.65	11.98	0.95
Iceland	17.14	-0.44	0.43	17.16	1.42	-5.81	4.08	-1.12	17.23	1.36
Norway	3.65	-1.75	-1.08	6.47	4.81	-0.52	0.95	-0.10	2.26	-0.93
Sweden	14.96	-0.38	0.01	15.33	1.89	-3.25	3.15	-0.92	13.35	1.12
Average	**8.79**	**-0.70**	**-0.26**	**9.75**	**1.62**	**-3.78**	**2.42**	**-0.76**	**9.54**	**0.72**
Western Europe:										
Austria	-1.56	0.52	-0.77	-1.31	-1.03	-4.21	3.06	-0.42	1.70	-0.41
Belgium	-2.91	-0.58	-0.06	-2.26	2.14	-0.16	-2.90	0.36	-1.45	-0.25
Switzerland	14.69	0.08	1.43	13.18	4.17	0.88	1.58	-0.15	7.07	-0.38
Germany	7.40	0.64	0.35	6.40	4.08	2.63	-2.93	0.29	2.37	-0.04
France	2.70	-0.82	-0.67	4.19	-0.20	8.06	-0.30	1.82	-4.11	-1.07
Ireland	-6.38	-0.73	-0.40	-5.25	-0.17	-5.50	2.28	-0.65	-0.11	-1.11
Luxembourg	0.00	1.04	-2.16	1.12	2.83	3.28	0.66	-0.03	-4.25	-1.38
Netherlands	6.51	0.93	-0.12	5.69	3.56	0.56	-1.86	0.49	3.57	-0.62
United Kingdom	6.97	0.47	0.07	6.44	3.65	-2.51	2.18	-0.65	4.57	-0.79
Average	**3.05**	**0.17**	**-0.26**	**3.13**	**2.11**	**0.34**	**0.20**	**0.12**	**1.04**	**-0.67**
Southern Europe:										
Cyprus	0.18	-1.79	-0.82	2.79	-6.65	7.45	6.16	1.71	-5.37	-0.52
Spain	-6.20	0.92	0.05	-7.17	-9.43	2.74	0.40	0.56	-3.55	2.11
Greece	-12.32	0.41	-0.06	-12.67	-5.12	0.40	-0.95	1.56	-8.31	-0.27
Italy	-13.21	0.47	-0.08	-13.60	-0.97	-2.13	-2.21	-0.72	-7.95	0.38
Malta	-7.18	-0.92	0.21	-6.48	6.06	-1.99	0.35	-0.96	-7.27	-2.67
Portugal	-3.55	-0.62	0.39	-3.31	-4.28	-7.27	0.38	0.48	6.35	1.03
Average	**-7.05**	**-0.25**	**-0.05**	**-6.74**	**-3.40**	**-0.13**	**0.69**	**0.44**	**-4.35**	**0.01**
Baltic States:										
Estonia	3.92	-1.87	-0.08	5.87	0.78	0.25	1.67	-0.40	3.98	-0.43
Lithuania	1.68	-1.46	-0.10	3.24	0.23	2.29	-0.08	0.40	0.52	-0.12
Latvia	1.61	-1.30	-0.04	2.96	-2.32	1.41	1.46	0.25	0.84	1.32
Average	**2.40**	**-1.55**	**-0.07**	**4.02**	**-0.44**	**1.32**	**1.02**	**0.09**	**1.78**	**0.26**
Eastern Europe:										
Bulgaria	-3.25	-1.02	-0.03	-2.21	-3.58	3.62	-1.70	2.06	-2.44	-0.17
Czech Republic	-0.82	-1.31	-1.30	1.79	1.50	3.98	-0.52	1.70	-4.61	-0.26
Croatia	-9.71	-1.16	-0.04	-8.51	-6.24	0.23	-4.69	1.75	-1.43	1.88
Hungary	-4.88	-1.70	-0.02	-3.17	-1.52	-0.88	2.18	-0.06	-2.59	-0.29
Poland	-5.98	-1.12	0.02	-4.89	-0.14	-0.86	-1.13	0.45	-3.15	-0.04
Romania	-1.93	-0.60	0.73	-2.07	8.27	3.80	-3.30	0.48	-8.74	-2.56
Slovenia	-1.00	-0.54	-0.30	-0.16	-0.14	7.94	-2.22	-1.25	-7.19	2.70
Slovakia	-1.39	-1.48	-0.41	0.50	1.54	0.16	-1.82	1.44	-1.13	0.31
Average	**-3.62**	**-1.11**	**-0.17**	**-2.34**	**-0.04**	**2.25**	**-1.65**	**0.82**	**-3.91**	**0.20**

NOTE: The entries in the table are employment gaps (relative to the population-weighted average of employment across countries) expressed in percentage point. The first column shows the raw employment gap; the second and third columns show the gap explained by differences in demographics and initial conditions, respectively; the fourth column shows the gap explained by differences in transition probabilities. The latter is decomposed into the gap explained by each transition probability in the remaining columns of the table. The last row of each country group reports the (unweighted) average of the numbers in each column.

B Model Appendix

B.1 Labor-market flows and distributions

- Let $n_{\tau,i}(k)$, $u_{\tau,i}(k)$, $\tau = 0, ..., T$ and $i \in \{0,1\}$ represent measures of individuals in non-participation and unemployment, age τ, UI status i. Let $e_{\tau,i}$ $\tau = 0, ..., T$ and $i \in \{0,1\}$ be the measure of employed individuals with age τ, EPL status i. In addition, $\tilde{\alpha}_{\tau,i} \in [0,1]$ $\tau = 0, ..., T$, $i \in \{0,1\}$ is the employment share of matches with revealed quality (given age τ and EPL status i).

- Let $\tilde{\mathcal{H}}_{z,\tau,i}(z|k)$, $k \in \mathcal{K}$, $\tau = 0, ..., T$, and $i \in \{0,1\}$ be the fraction of unrevealed-quality matches with stochastic match-output component $\tilde{z} \leq z$, $z \in \mathcal{Z}$, conditional on human capital k, age τ, and EPL status i. Moreover, $\mathcal{H}_{z,\tau,i}(z|\, k, x)$ is the same fraction, but considering the revealed-quality matches and conditioning on match quality $x \in \mathcal{X}$.

- In addition, $\mathcal{H}_{x,\tau,i}(x|\, k)$ is the fraction of matches with (revealed) quality $\tilde{x} \leq x \in \mathcal{X}$ conditional on age and EPL status.

- Lastly, let $\tilde{h}_{z,\tau,i}(.\,|\, k)$, $h_{z,\tau,i}(.\,|\, k, x)$ and $h_{x,\tau,i}(.\,|\, k)$ be the equilibrium density functions associated with the above defined c.d.f.

- Define $\lambda_{\tau,nn,i} \equiv 1 - \lambda_{\tau,nu,i} - \lambda_{\tau,ne,i}$, $\lambda_{\tau,uu,i} \equiv 1 - \lambda_{\tau,un,i} - \lambda_{\tau,ue,i}$, and $\lambda_{\tau,ee,i} \equiv 1 - \lambda_{\tau,en,i} - \lambda_{\tau,eu,i}$ for $i \in \{0,1\}$ and $\tau = 0, ..., T-1$.

Aggregate labor market flows. *Non-participation outflow rates:*

$$\Lambda_{nj} = \sum_{\tau=0}^{T-1} \sum_{i \in \{0,1\}} \sum_{k \in \mathcal{K}} \frac{n_{\tau,i}(k)}{\mathcal{L}_n} \lambda_{\tau,nj,i}(k) \tag{B.1}$$

for all destination state $j \in \{u, e\}$ (flows into unemployment and employment).

Unemployment outflow rates:

$$\Lambda_{uj} = \sum_{\tau=0}^{T-1} \sum_{i \in \{0,1\}} \sum_{k \in \mathcal{K}} \frac{u_{\tau,i}(k)}{\mathcal{L}_u} \lambda_{\tau,uj,i}(k) \tag{B.2}$$

for all destination state $j \in \{n, e\}$ (flows into nonparticipation and employment).

Employment:

$$\begin{aligned}\Lambda_{ej} = \sum_{\tau=0}^{T-1} \sum_{i \in \{0,1\}} \sum_{k \in \mathcal{K}} \Bigg[& \frac{\tilde{\alpha}_{\tau,i} e_{\tau,i}(k)}{\mathcal{L}_e} \int_{x \in \mathcal{X}} \left(\int_{z \in \mathcal{Z}} \lambda_{\tau,ej,i}(k, x, z) d\mathcal{H}_{z,\tau,i}(z|k, x) \right) d\mathcal{H}_{x,\tau,i}(x|k) \\ & + \frac{(1 - \tilde{\alpha}_{\tau,i}) e_{\tau,i}(k)}{\mathcal{L}_e} \int_{z \in \mathcal{Z}} \tilde{\lambda}_{\tau,ej,i}(k, z) d\tilde{\mathcal{H}}_{z,\tau,i}(z|k) \Bigg] \end{aligned} \tag{B.3}$$

(B.4)

for all destination state $j \in \{n,u\}$ (flows into nonparticipation and unemployment).

Distributions. Probability of transiting from $j \in \{n,u\}$, $i \in \{0,1\}$, $k \in \mathcal{K}$ to $l \in \{n,u\}$, $i' \in (0,1)$, $k' \in \mathcal{K}$ between age τ and $\tau+1$:

$$\xi_{\tau,jl,ii'}(k'|k) = \mu_o(i'|i)\pi_o(k'|k)\left[1 - s^*_{j,\tau,i}(k)p(\theta)\mathcal{I}(k' \geq \underline{k}_{\tau+1,j,i'})\right]\mathcal{P}^{jl}_{\tau+1,i'}(k') \tag{B.5}$$

Probability of transiting from $j \in \{n,u\}$, $i \in \{0,1\}$, $k \in \mathcal{K}$ to e (unrevealed), $(k',z',i') \in \mathcal{K} \times \{z_0\} \times \{0\}$ between age τ and $\tau+1$:

$$\xi_{\tau,je,ii'}(k',z'|k) = \pi_o(k'|k)s^*_{j,\tau,i}(k)p(\theta)\sum_{i''\in\{0,1\}}\mu_o(i''|i)\mathcal{I}\big(\,k' \geq \underline{k}_{j,\tau+1,i''}\,\big). \tag{B.6}$$

The probability of transiting to revealed-quality employment from nonemployment is zero by assumption (match are experience goods). Similarly, the probability of transiting to $(z',i') \in \big(\mathcal{Z} \setminus \{z_0\}\big) \times \{1\}$ is zero (z_0 is the starting match productivity and new match start with EPL regime $i = 0$).

Probability of transiting from e (unrevealed), state $(k,z,i) \in \mathcal{K} \times \mathcal{Z} \times \{0,1\}$ to $j \in \{n,u\}$, $(k',i') \in \mathcal{K} \times \{0\}$:

$$\begin{aligned}&\tilde{\xi}_{\tau,ej,ii'}(k'|k,z) = \\ &\pi_e(k'|k)\sum_{i''\in\{0,1\}}\mu_e(i''|i)\left[(1-\alpha)G_z\big(\tilde{\underline{z}}_{\tau+1,i''}(k')|z\big) + \alpha\int_{x'\in\mathcal{X}}G_z\big(\underline{z}_{\tau+1,i''}(k',x')|z\big)dG_x(x')\right]\mathcal{P}^{ej}_{\tau+1}(k')\end{aligned} \tag{B.7}$$

Note that the probability of transiting to UI state $i' = 0$ is zero (newly nonemployed workers start with high UI benefits indexed by $i' = 1$).

Density transiting from e (revealed), state $(k,x,z,i) \in \mathcal{K} \times \mathcal{X} \times \mathcal{Z} \times \{0,1\}$ to $j \in \{n,u\}$, $(k',i') \in \mathcal{K} \times \{0\}$:

$$\xi_{\tau,ej,ii'}(k'|k,x,z) = \pi_e(k'|k)\sum_{i'\in\{0,1\}}\mu_e(i'|i)G_z\big(\underline{z}_{\tau+1,i'}(k',x)|z\big)\mathcal{P}^{ej}_{\tau+1}(k') \tag{B.8}$$

Density transiting from e (unrevealed), state (k,z,i) to e (unrevealed), state (k',z',i'):

$$\tilde{\tilde{\xi}}_{\tau,ee,ii'}(k',z'|k,z) = (1-\alpha)\pi_e(k'|k)\mu_e(i'|i)\mathcal{I}(z' \geq \tilde{\underline{z}}_{\tau+1,i'}(k'))g_z(z'|z) \tag{B.9}$$

Density transiting from e (unrevealed) to e (revealed):

$$\tilde{\xi}_{\tau,ee,ii'}(k',x',z'|k,z) = \alpha g_x(x')\pi_e(k'|k)\mu_e(i'|i)\mathcal{I}(z' \geq \underline{z}_{\tau+1,i'}(k',x'))g_z(z'|z) \tag{B.10}$$

Density transiting from e (revealed) to e (revealed):

$$\xi_{\tau,ee,ii'}(k',x',z'|k,x,z) = \mathcal{I}(x'=x)\pi_e(k'|k)\mu_e(i'|i)\mathcal{I}(z' \geq \underline{z}_{\tau+1,i'}(k',x'))g_z(z'|z). \tag{B.11}$$

Nonparticipation stock, by age and skill:

$$
\begin{aligned}
n_{\tau+1,i'}(k') &= \sum_i \sum_k \left(\xi_{\tau,nn,ii'}(k'|k) n_{\tau,i}(k) + \xi_{\tau,un,ii'}(k'|k) u_{\tau,i}(k) \right) \\
&\quad + \mathcal{I}(i'=1) \sum_i \sum_k \Bigg[(1-\tilde{\alpha}_{\tau,i}) \int_z \tilde{\xi}_{\tau,en,ii'}(k'|k,z) d\tilde{\mathcal{H}}_{z,\tau,i}(z|k) \\
&\qquad + \tilde{\alpha}_{\tau,i} \int_x \int_z \xi_{\tau,en,ii'}(k'|k,x,z) d\mathcal{H}_{z,\tau,i}(z|k,x) d\mathcal{H}_{x,\tau,i}(x|k) \Bigg] e_{\tau,i}(k)
\end{aligned}
\tag{B.12}
$$

for all $k' \in \mathcal{K}$, $i' = 0, 1$, and $\tau = 2, ..., T-1$. Unemployment:

$$
\begin{aligned}
u_{\tau+1,i'}(k') &= \sum_i \sum_k \left(\xi_{\tau,nu,ii'}(k'|k) n_{\tau,i}(k) + \xi_{\tau,uu,ii'}(k'|k) u_{\tau,i}(k) \right) \\
&\quad + \mathcal{I}(i'=1) \sum_i \sum_k \Bigg[(1-\tilde{\alpha}_{\tau,i}) \int_z \tilde{\xi}_{\tau,eu,ii'}(k'|k,z) d\tilde{\mathcal{H}}_{z,\tau,i}(z|k) \\
&\qquad + \tilde{\alpha}_{\tau,i} \int_x \int_z \xi_{\tau,eu,ii'}(k'|k,x,z) d\mathcal{H}_{z,\tau,i}(z|k,x) d\mathcal{H}_{x,\tau,i}(x|k) \Bigg] e_{\tau,i}(k)
\end{aligned}
\tag{B.13}
$$

for all $k' \in \mathcal{K}$, $i' = 0, 1$, and $\tau = 2, ..., T-1$.

Employment stocks. Density of individuals of age $\tau + 1$, employed in a job with unrevealed match quality, and with state (k', z', i'):

$$
\begin{aligned}
(1-\tilde{\alpha}_{\tau+1,i'}) e_{\tau+1,i'}(k') \tilde{h}_{z,\tau+1,i'}(z'|k') &= \tilde{\tilde{\xi}}_{\tau,ee,ii'}(k',z'|k,z)(1-\tilde{\alpha}_{\tau,i}) e_{\tau,i}(k) \tilde{h}_{z,\tau,i}(z|k) \\
&\quad + \mathcal{I}(z'=z_0, i'=0) \sum_i \left(\xi_{\tau,ne,i}(k'|k) n_{\tau,i}(k) + \xi_{\tau,ue,i}(k'|k) u_{\tau,i}(k) \right)
\end{aligned}
\tag{B.14}
$$

for $(k', z') \in \mathcal{K} \times \mathcal{Z}$, $i' = 0, 1$, and $\tau = 2, ..., T-1$. Density of individuals of age $\tau+1$, employed in a job with revealed match quality, and with state (k', x', z', i'):

$$
\begin{aligned}
&\tilde{\alpha}_{\tau+1,i'} e_{\tau+1,i'}(k') h_{z,\tau+1,i'}(z'|k',x') h_{x,\tau+1,i'}(x'|k') = \\
&\left(\xi_{\tau,ee,ii'}(k',x',z'|k,x,z) \tilde{\alpha}_{\tau,i} h_{z,\tau,i}(z|k,x) h_{x,\tau,i}(x|k) + \tilde{\xi}_{\tau,ee,ii'}(k',x',z'|k,z)(1-\tilde{\alpha}_{\tau,i}) \tilde{h}_{z,\tau}(z|k) \right) e_{\tau,i}(k).
\end{aligned}
\tag{B.15}
$$

for $(k', x', z') \in \mathcal{K} \times \mathcal{Z} \times \mathcal{X}$, $i' = 0, 1$, and $\tau = 2, ..., T-1$. Initial conditions:

$$
\begin{aligned}
n_0(k) &= \frac{1}{T+1} \mathcal{I}(k = k_0); & n_1(k') &= \pi_o(k'|k) \, \mathcal{P}^{nn}_{1,0}(k') \\
u_0(k) &= 0; & u_1(k') &= \pi_o(k'|k) \, \mathcal{P}^{nu}_{1,0}(k') \\
e_0(k) &= 0; & e_1(k') &= 0,
\end{aligned}
\tag{B.16}
$$

for all $k, k' \in \mathcal{K}$.

B.2 Numerical resolution

- Consider discretized sets approximating $\mathcal{Z}$ and $\mathcal{X}$. Denote these sets by $\hat{\mathcal{Z}}$ and $\hat{\mathcal{X}}$. Let I_k, I_x, I_z be the size/cardinality of sets $\mathcal{K}$, $\hat{\mathcal{X}}$, and $\hat{\mathcal{Z}}$.

- Define the vectors with elements equal to age-specific nonemployment measures across states:

$$\begin{aligned} \mathbf{n}_\tau &= \left\{ n_{\tau,i}(k) \,:\, (k,i) \in \mathcal{K} \times \{0,1\} \right\} \\ \mathbf{u}_\tau &= \left\{ u_{\tau,i}(k) \,:\, (k,i) \in \mathcal{K} \times \{0,1\} \right\} \end{aligned} \tag{B.17}$$

  for $\tau = 0, ..., T$.

- With an abuse of notation, define the age-specific employment measure vectors:

$$\begin{aligned} \tilde{\mathbf{e}}_\tau &= \left\{ (1-\tilde{\alpha}_{\tau,i}) e_{\tau,i}(k) \tilde{h}_{z,\tau}(z|k) \,:\, (k,z,i) \in \times\mathcal{K} \times \hat{\mathcal{Z}} \times \{0,1\} \right\} \\ \mathbf{e}_\tau &= \left\{ \tilde{\alpha}_{\tau,i} e_{\tau,i}(k) h_{z,\tau}(z|k,x) h_{x,\tau}(x|k) \,:\, (k,x,z,i) \in \times\mathcal{K} \times \hat{\mathcal{X}} \times \hat{\mathcal{Z}} \times \{0,1\} \right\}. \end{aligned} \tag{B.18}$$

  for $\tau = 0, ..., T$.

- Define the nonemployment-to-nonemployment transition matrices:

$$\mathbf{\Gamma}_{\tau,jl} = \left\{ \xi_{\tau,jl,ii'}(k'|k) \,:\, (k,i) \in \mathcal{K} \times \{0,1\}; (k',i') \in \mathcal{K} \times \{0,1\} \right\} \tag{B.19}$$

  for all $j, l \in \{n, u\}$ and $\tau = 0, ..., T-1$.

- Nonemployment to employment (unrevealed quality):

$$\mathbf{\Gamma}_{\tau,je} = \left\{ \xi_{\tau,jl,ii'}(k',z'|k) \,:\, (k,i) \in \mathcal{K} \times \{0,1\}; (k',z',i') \in \mathcal{K} \times \hat{\mathcal{Z}} \times \{0,1\} \right\} \tag{B.20}$$

  for all $j \in \{n, u\}$ and $\tau = 0, ..., T-1$

- Employment to nonemployment (from unrevealed- and revealed-quality, respectively):

$$\begin{aligned} \tilde{\mathbf{\Gamma}}_{\tau,ej} &= \left\{ \tilde{\xi}_{\tau,ej,ii'}(k'|k,z) \,:\, (k,z,i) \in \mathcal{K} \times \hat{\mathcal{Z}} \times \{0,1\}; (k',i') \in \mathcal{K} \times \{0,1\} \right\} \\ \mathbf{\Gamma}_{\tau,ej} &= \left\{ \tilde{\xi}_{\tau,ej,ii'}(k'|k,x,z) \,:\, (i,k,x,z) \in \mathcal{K} \times \{0,1\} \times \hat{\mathcal{X}} \times \hat{\mathcal{Z}}; (k',i') \in \mathcal{K} \times \{0,1\} \right\} \end{aligned} \tag{B.21}$$

  for all $j \in \{n, u\}$ and $\tau = 2, ..., T-1$.

- Employment to employment:

$$
\begin{aligned}
\tilde{\tilde{\mathbf{\Gamma}}}_{\tau,ee} &= \left\{ \tilde{\tilde{\xi}}_{\tau,ee,ii'}(k',z'|k,z) \,:\, (k,z,i) \in \mathcal{K} \times \hat{\mathcal{Z}} \times \{0,1\}; (k',z',i') \in\in \mathcal{K} \times \hat{\mathcal{Z}} \times \{0,1\} \right\} \\
\tilde{\mathbf{\Gamma}}_{\tau,ee} &= \left\{ \tilde{\xi}_{\tau,ee,ii'}(k',x',z'|k,z) \,:\, (k,z,i) \in \mathcal{K} \times \hat{\mathcal{Z}} \times \{0,1\}; (k',x',z',i') \in \mathcal{K} \times \hat{\mathcal{X}} \times \hat{\mathcal{Z}} \times \{0,1\} \right\} \\
\mathbf{\Gamma}_{\tau,ee} &= \left\{ \tilde{\xi}_{\tau,ee,ii'}(k',x',z'|k,x,z) \,:\, (k,x,z,i),\ (k',x',z',i') \in \mathcal{K} \times \hat{\mathcal{X}} \times \hat{\mathcal{Z}} \times \{0,1\} \right\}
\end{aligned}
\tag{B.22}
$$

for all $\tau = 2, ..., T-1$. These represent, respectively, transition matrices from unrevealed-quality employment to unrevealed-quality, unrevealed to revealed and revealed to revealed.

- In matrix form, the discretized equilibrium distributions satisfy the system:

$$
\begin{aligned}
\mathbf{n}_\tau &= \mathbf{\Gamma}_{\tau-1,nn}\,\mathbf{n}_{\tau-1} + \mathbf{\Gamma}_{\tau-1,un}\,\mathbf{u}_{\tau-1} + \tilde{\mathbf{\Gamma}}_{\tau-1,en}\,\tilde{\mathbf{e}}_{\tau-1} + \mathbf{\Gamma}_{\tau-1,en}\,\mathbf{e}_{\tau-1} \\
\mathbf{u}_\tau &= \mathbf{\Gamma}_{\tau-1,nu}\,\mathbf{n}_{\tau-1} + \mathbf{\Gamma}_{\tau-1,uu}\,\mathbf{u}_{\tau-1} + \tilde{\mathbf{\Gamma}}_{\tau-1,eu}\,\tilde{\mathbf{e}}_{\tau-1} + \mathbf{\Gamma}_{\tau-1,eu}\,\mathbf{e}_{\tau-1} \\
\tilde{\mathbf{e}}_\tau &= \mathbf{\Gamma}_{\tau-1,ne}\,\mathbf{n}_{\tau-1} + \mathbf{\Gamma}_{\tau-1,ue}\,\mathbf{u}_{\tau-1} + \tilde{\tilde{\mathbf{\Gamma}}}_{\tau-1,ee}\,\tilde{\mathbf{e}}_{\tau-1} \\
\mathbf{e}_\tau &= \tilde{\mathbf{\Gamma}}_{\tau-1,ee}\,\mathbf{e}_{\tau-1} + \mathbf{\Gamma}_{\tau-1,ee}\,\mathbf{e}_{\tau-1},
\end{aligned}
\tag{B.23}
$$

for $\tau = 2, ..., T$, with initial values given by conditions (B.16).

- The critical task for numerical implementation is to construct the transition matrices. Ideally, this construction should be "vectorized" for faster computation (i.e., expressed in terms of vector and matrix operations). With an abuse of notation, let μ_o, μ_e, π_o, and π_e represent transition matrices for the UI regime, the EPL regime, the out-of-work and employed skill dynamics, respectively. Define the policy-function vectors:

$$
\begin{aligned}
\mathbf{s}_{\tau,j,i} &= \left\{ s_{\tau,j,i}(k) \,:\, k \in \mathcal{K} \right\}; && j \in \{n,u\} \\
\mathbf{P}^{jl}_{\tau,i} &= \left\{ \mathcal{P}^{jl}_{\tau,i}(k) \,:\, k \in \mathcal{K} \right\}; && j,l \in \{n,u\} \\
\mathbf{P}^{ej}_{\tau} &= \left\{ \mathcal{P}^{ej}_{\tau}(k) \,:\, k \in \mathcal{K} \right\}; && j \in \{n,u\} \\
\gamma_{\tau,je,i} &= \left\{ \mathcal{I}\big(k \geq \underline{k}_{\tau,j,i}\big) \,:\, k \in \mathcal{K} \right\}; && j \in \{n,u\} \\
\tilde{\gamma}_{\tau,i} &= \left\{ \mathcal{I}\big(z \geq \tilde{\underline{z}}_{\tau,i}(k)\big) \,:\, (k,z) \in \mathcal{K} \times \mathcal{Z} \right\} \\
\gamma_{\tau,i} &= \left\{ \mathcal{I}\big(z \geq \underline{z}_{\tau,i}(k,x)\big) \,:\, (k,x,z) \in \mathcal{K} \times \mathcal{X} \times \mathcal{Z} \right\}
\end{aligned}
\tag{B.24}
$$

for all $\tau = 1, ..., T$, $i \in \{0,1\}$. In addition, let $\hat{g}_x$ represent the p.m.f. associated with discretized match quality $x \in \hat{X}$ and let $\hat{P}_z$ be the transition matrix associated with the stochastic match-output component. Finally, $\hat{g}_z$ is a vector of size I_z with zeros everywhere and with a one when $z = z_0$ (i.e., the entry level match quality). [TBC]

C Model fit to data

C.1 Model fit to non-targeted transition probabilities by age, gender and country

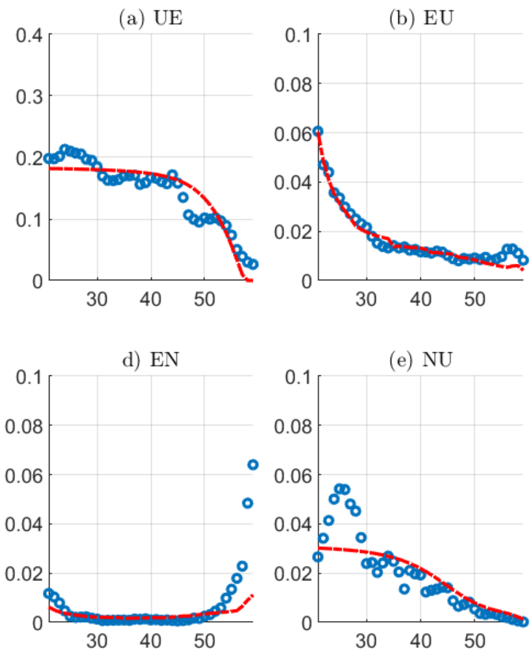

Figure C1: Transition probabilities: data and model simulation for France, men

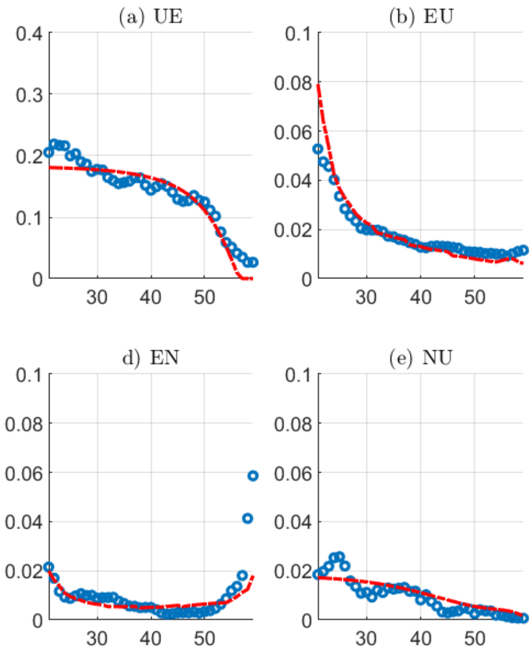

Figure C2: Transition probabilities: data and model simulation for France, women

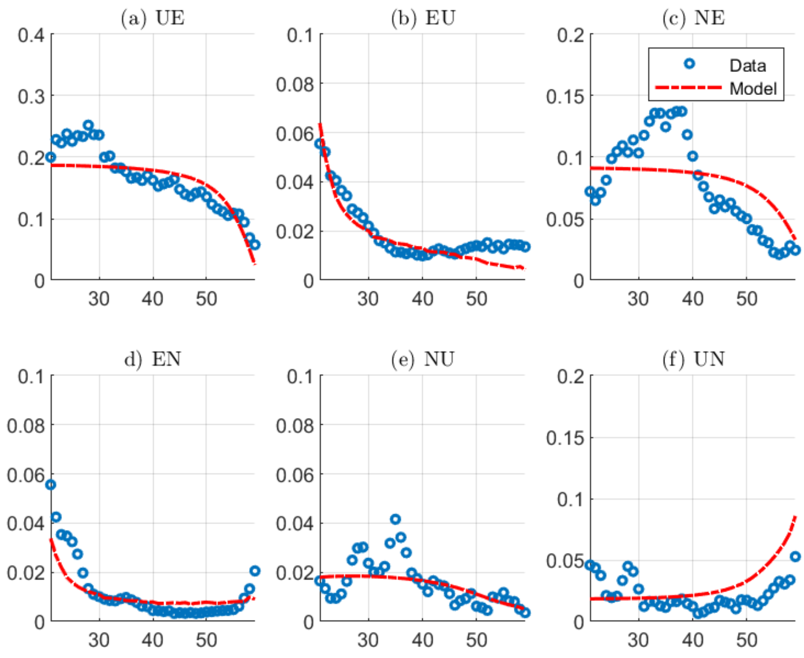

Figure C3: Transition probabilities: data and model simulation for Germany, men

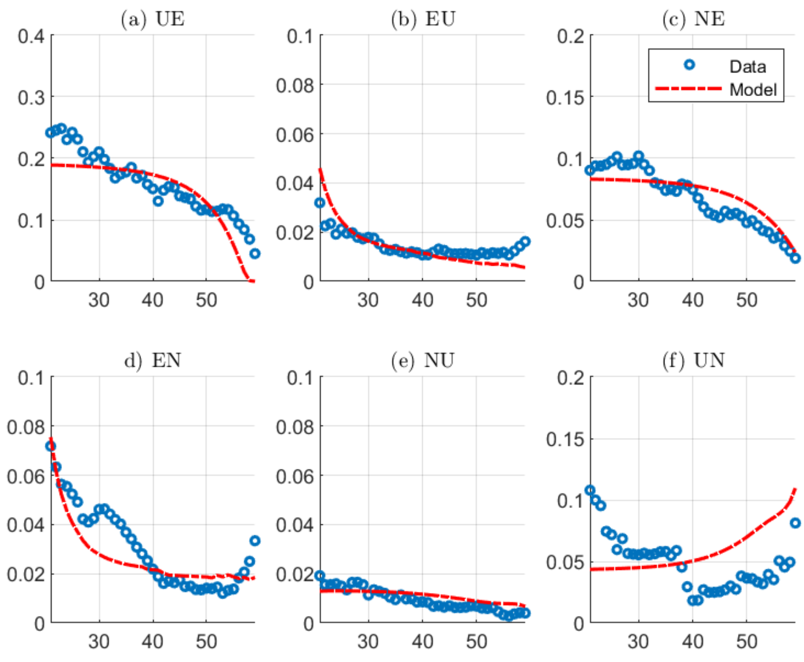

Figure C4: Transition probabilities: data and model simulation for Germany, women

C.2 Life-cycle cross-country variance profiles

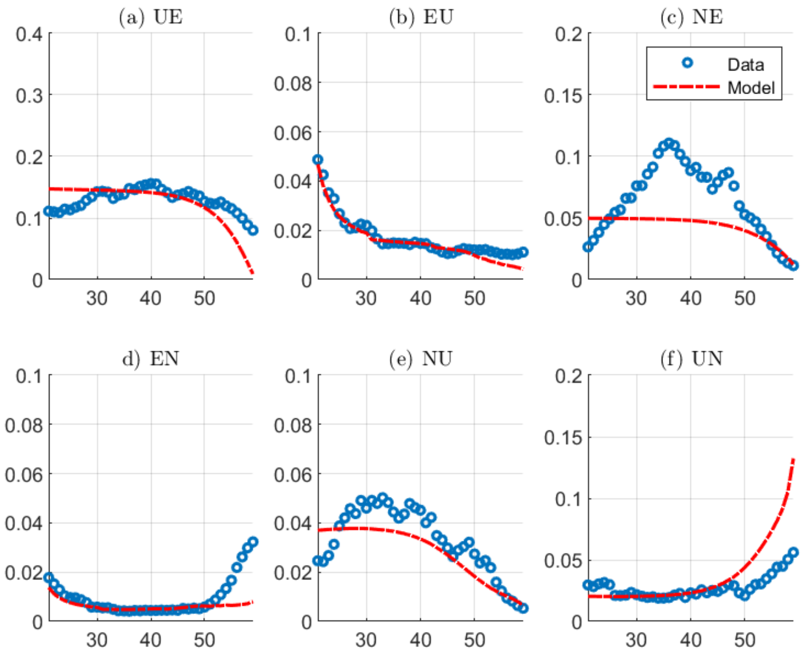

Figure C5: Transition probabilities: data and model simulation for Italy, men

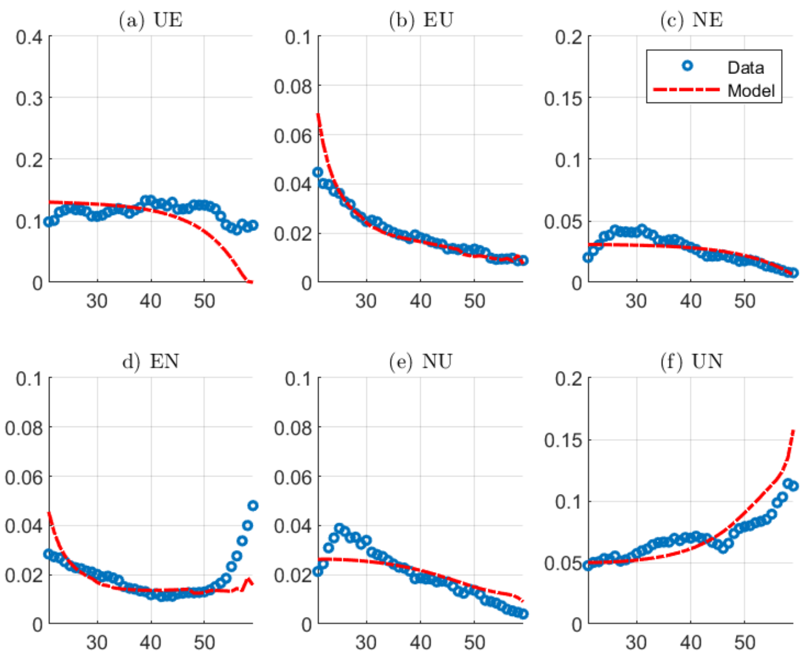

Figure C6: Transition probabilities: data and model simulation for Italy, women

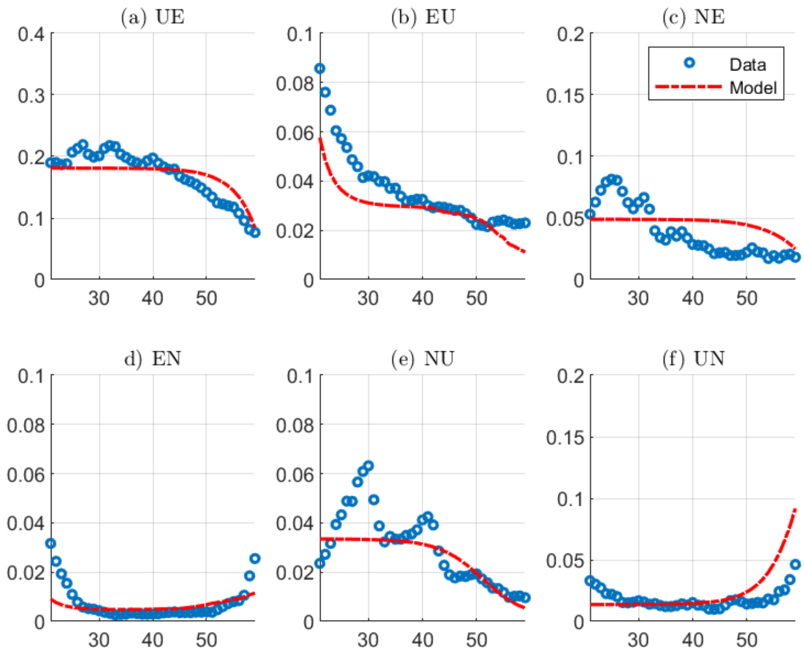

Figure C7: Transition probabilities: data and model simulation for Spain, men

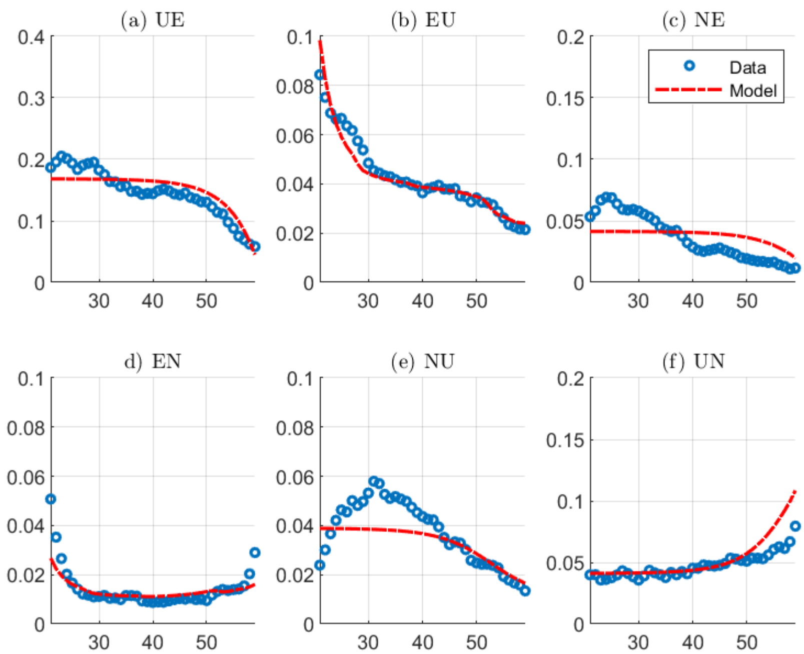

Figure C8: Transition probabilities: data and model simulation for Spain, women

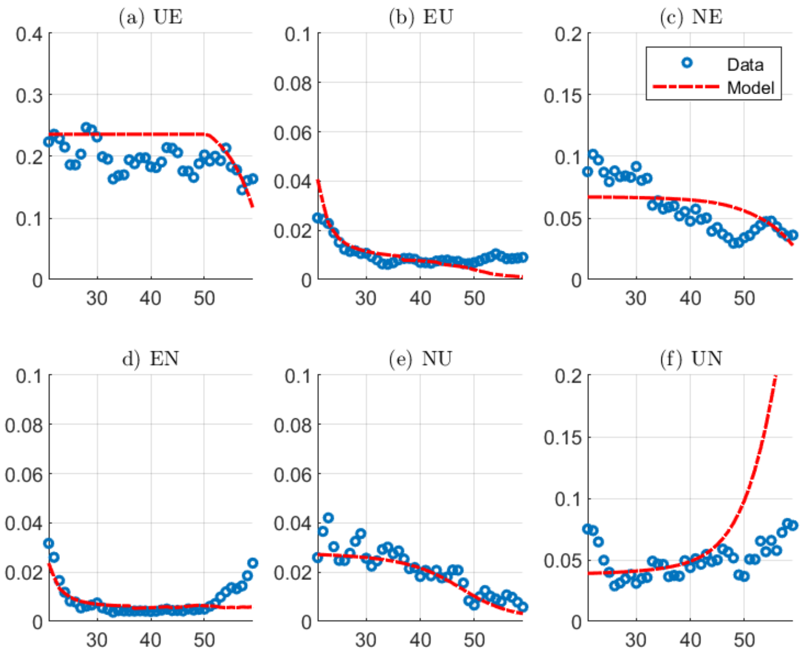

Figure C9: Transition probabilities: data and model simulation for the U.K., men

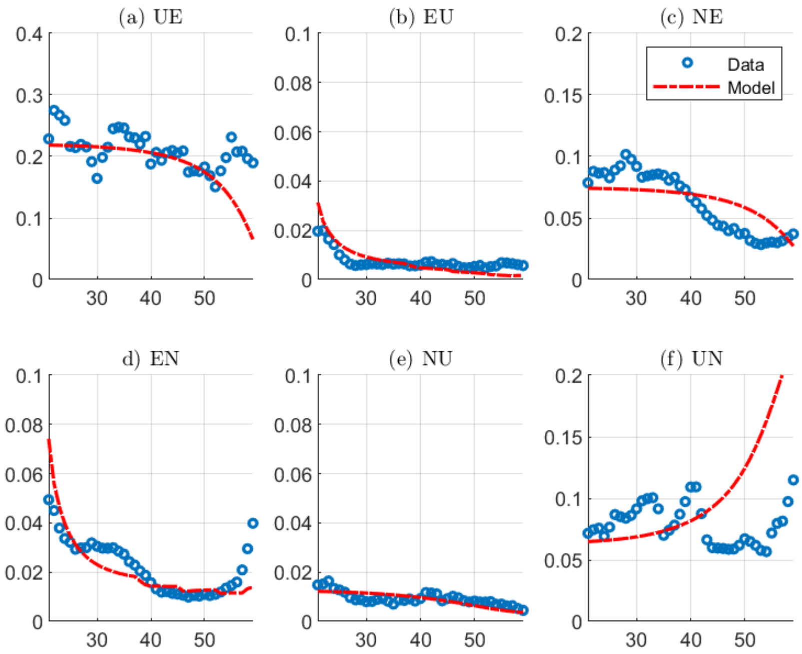

Figure C10: Transition probabilities: data and model simulation for the U.K., women

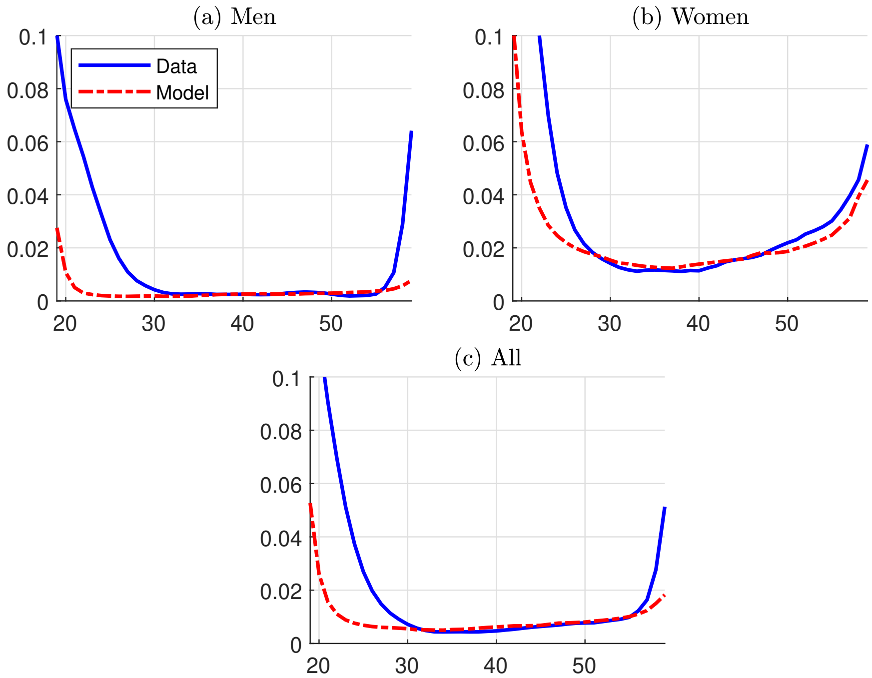

Figure C11: Employment life-cycle cross-country (big 5) variance, data and model

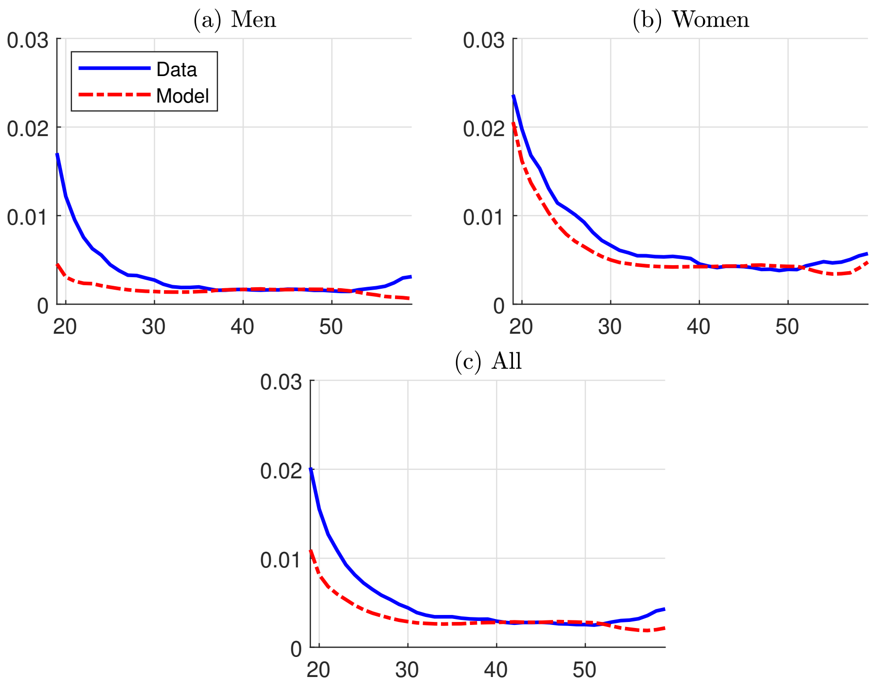

Figure C12: Unemployment life-cycle cross-country (big 5) variance, data and model